Climate change uncertainty evaluation, impacts modelling and resilience of farm scale dynamics in Scotland.

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Abstract

This Thesis explored a range of approaches to study the uncertainty and impacts associated with climate change at the farm scale in Scotland. The research objective was to use a process of uncertainty evaluation and simulation modelling to provide evidence of how primary production components of agriculture in Scotland may change under a future climate. The work used a generic Integrated Modelling Framework to structure the following sequence of investigations:

- Evaluate a Regional Climate Model's hindcast estimates (1960-1990) against observed weather data;
- Develop bias correction 'downscaling factors' to be applied to the Regional Climate Model's future estimates;
- Evaluate the impacts of weather data sources (observed and modelled) on estimates made by a cropping systems model (CropSyst);
- Estimate values for a range of agro-meteorological metrics using observed and estimated downscaled future weather data;
- Simulate spring barley and winter wheat growth using CropSyst with observed and modelled weather data;
- Develop CropSyst in order to represent grass growth, evaluate estimates against a set of *a priori* criteria and determine suitability for use in a whole farm model.
- Conduct counter-factual assessments of the impacts of climate change and potential adaptation options using a whole farm model (LADSS).

The study aimed to use tools on a spectrum of land use modelling complexity: agro-meteorological metrics (simple), CropSyst (intermediate), and the whole-farm integrated model (complex). Such an approach had a path dependency, in that to use the livestock system model component within the whole farm model, CropSyst had to make estimates of an acceptable quality for grass production. CropSyst however failed to meet the *a priori* evaluation criteria. This, coupled with technical and time constraints in running LADSS, led to the decision not to run the whole farm model.

The findings were organised within the concepts of resilience and adaptive capacity. Results gained showed that the HadRM3 Regional Climate Model was capable of making both good and poor estimates of weather variables in the UK, and that downscaling improved the match between hindcast and observed weather data significantly. A sensitivity analysis involving introducing uncertainty from weather data sources within CropSyst showed that care was needed in interpreting estimates of future crop production. The agro-meteorological metrics indicated that whilst growing season length increases, the date of end of field capacity does not. The projected changes in crop production will likely be more positive if crop responses to elevated CO_2 are considered. However, there will be additional constraints on crop growth due to increases in duration and magnitude of periods of growth limiting soil water deficits. Without adaptation to crop varieties with slower phenological development, yield decreases are seen in spring barley and winter wheat.

The thesis concludes, whilst recognising the caveats and limitations of the methods used and the multiple range of external influencing issues, that the biophysical impacts at the farm scale in Scotland are within the boundaries of resilience, given that achievable adaptation options exist and are undertaken. The dynamics of farm scale management will need to adjust to cope with higher levels of water stress, but opportunities will also arise for greater

flexibility in land use mixes. Crop yield can increase due to more favourable growing conditions and cultivar adaptations. These conclusions, when placed within the context of climate change impacts and adaptive cycles at a global scale, indicate that agriculture in Scotland has the potential to cope with the impacts but that substantial changes are required in farming practices.

Declaration

I declare that I have composed this thesis. The work is my own but was conducted within a research group (http://www.macaulay.ac.uk/LADSS/). Colleagues have contributed to material within this thesis and are acknowledged below. Chapters 3 and 5 are based on published papers, and Chapter 4 on a submitted paper, where I was the lead author within the research group. To the best of my knowledge the text within this thesis, where also occurring in published papers written by the research group, is my own (or has been edited by co-authors and or journal editors). Additionally some of the material used was based on work done prior to matriculation, but this is referenced accordingly.

Specifically, Kevin Buchan provided technical support to enable conversion of observed weather data and HadRM3 Regional Climate Model data into an Oracle database. The various agro-meteorological metrics were developed by the research group based on existing methods. Kevin implemented the calculation of the agro-meteorological metrics within Oracle and structured queries to enable data extraction to analyse results. He and Dr Keith Matthews also developed the soil water balance model used within Chapter 5 and produced the originals of Figures 31, 32 and 33. Dr Matthews also produced the original versions on which Figures 27, 29 and 30 are based, and created the original of Table 9.

Mr Dave Miller provided support in automating the calculation of the downscaling factors used in Chapter 3, and assisted in running the calculation processes to downscale the HadRM3 data. He also produced Figure 3.

Signed:

Date: 6th July 2010

Acknowledgements

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A particular note of gratitude goes to Dr Claudio Stöckle and his team at Washington State University for his help and assistance in developing the grass modelling capabilities of the CropSyst cropping systems model. Dr Kevin Marsh at the British Atmospheric Data Centre was invaluable in providing the climate model data through the LINK project. I would also like to thank the UK Meteorological Office for the use of the MIDAS observed weather data. Thanks to Dr Desiree Romer at the Scottish Agricultural College who provided data of the three-cut silage system at Crichton Farm, and to SAC for use of the grass trials data.

And finally, my gratitude goes to my wife Beth for her support and tolerance, and our children Jenim and Joe, for putting up with my grumpiness.

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Abbreviations used

ActET	Actual evapotranspiration (mm)
AD	Air dried (soil)
AFC	Adapted future cultivar
Agro-metrics	Agro-meteorological metrics
AOGCM	Atmosphere-Ocean General Circulation Models
BADC	British Atmospheric Data Centre (http://badc.nerc.ac.uk/home/index.html)
CC	Climate change
CD	Campbell – Donatelli model (solar radiation estimation based on temperature)
CDF	Cumulative distribution function
CET	Central England Temperature
DsFP	Downscaled future projection (downscaled estimates from the HadRM3 for the period 2070 to 2100)
DsH	Downscaled hindcast data (from the HadRM3)
EMIC	Earth Systems Models of Intermediate Complexity
FC	Field capacity (mm)
GAI	Leaf Green Area Index (unitless)
GCM	Global Circulation Model
GHG	Greenhouse gas
GDD	Growing degree days (thermal time accumulation) (°C day)
HadRM3	Hadley Centre Regional Climate Model
IA	Integrated Assessment
IMF	Integrated Modelling Framework
J-W	Johnson Woodward model (sunshine duration to solar radiation conversion)
LADSS	Land Allocation Decision Support System
LAI	Leaf Area Index (unitless)
LSM	Livestock Systems Model
PWP	Permanent wilting point (mm)
Obs	Observed (referring to weather data)
OFP	Original future projection (original estimates from the HadRM3 for the period 2070 to 2100)
OH	Original Hindcast (raw estimates from the HadRM3 for the period 1960 to 1990)
P	Precipitation (mm)
PAW	Plant available water
PotET	Potential evapotranspiration (mm)
PWP	Permanent wilting point
RCM	Regional Climate Model
RST	Resource Scheduling Tool
SAC	Scottish Agricultural College
SCM	Simple Climate Model
SES	Socio-ecological systems
SMD	Soil moisture deficit (mm)
SP	Saturation point (mm)
SR	Surface runoff (mm)

SRES	Special Report on Emissions Scenarios
S_o	Total downward surface shortwave flux (direct and diffuse solar radiation) (MJ m^2 day^{-1})
SWB	Soil water balance model
Tmax	Maximum temperature
Tmin	Minimum temperature
UNFCCC	United Nations framework Convention on Climate Change
WSI	Water Stress Index (unitless)

Sites used: (refer to Figure 2)

Abd	Aberdeen
Abe	Aberporth
Ald	Aldergrove
Auc	Auchincruive
Avi	Aviemore
Bra	Bracknell
Carn	Carnwath
Caw	Cawood
Duns	Dunstaffnage
Eas	East Malling
Esk	Eskdalemuir
Eve	Everton
Gal	Galashiels
Inv	Inverness
Ler	Lerwick
Myln	Mylnefield
Roth	Rothamsted
Sut	Sutton Bonington
Wal	Wallingford

Chapter 1: Introduction.

1.1 Defining the problem and scope of the study.

Changes in the biophysical environment as a result of climate change are likely to require substantial adaptations within current farming systems. Climate change has been recognised as the primary challenge facing human society in the immediate future (Pachauri 2004, IPCC 2007a, Rockstrőm *et al.* 2009) where the maintenance of a viable, sustainable agricultural sector is crucial (Easterling *et al.* 2007). Climate information has been recognised as a vital component in planning for climate change impacts and adaptation (Munang *et al.* 2009).

This study aims to investigate the potential impacts of climate change on farm-scale dynamics in Scotland and explore adaptation options by taking a holistic Integrated Assessment approach (Rivington *et al.* 2006a) using a range of tools within an Integrated Modelling Framework (IMF) (Matthews *et al.* 1999, Rivington *et al.* 2007,). An IMF can be seen as a flexible structure that facilitates inter-disciplinarily research and allows the integration of tools and methods covering a range of spatial and temporal scales (see further details in Chapter 2, section 2.10). Farm-scale dynamics are defined as the relationships and interactions between the various components (soils, enterprise mixes, infrastructure etc.) that make up the farm and how they are managed. In this study a ‘farm’ can be defined as ‘mixed’ (with both arable and livestock with on-farm produced grass). The problem to be defined is that there is need to transfer climate change issues from a global scale to Scotland, and the variations in bioclimatic zones within it, in order to develop adaptations to farming that are appropriate for individual locations. Similarly there is need to have information on the consequences of impacts across the whole United Kingdom in order to put localised impacts and adaptations within a national and international context. Adaptations need to integrate with changes in the climate whilst considering legislative obligations to achieve national level mitigation (i.e. 2008 Scottish Climate Change Bill[1] or global level aspirations such as the UNFCCC 'Copenhagen Accord'[2]), and responses by market forces operating within rapidly changing economic circumstances.

The fundamentals of projecting into the future of how agriculture will function has to consider the issue of uncertainty. This can be categorised into basic issues of certainty, manageable uncertainty and irreducible uncertainty. The only usable certainty is what has happened in the past, manageable uncertainty is knowing what we have to work with at the moment (natural resources, policies, market conditions, skills etc.). Irreducible uncertainty is concerned with those issues that are of greatest importance but have severe limitations in our ability to reduce uncertainty or predict possible outcomes. Uncertainty examples include:

- Solar activity; energy fluxes and spectral variations.
- Climate modelling; parameters, structure, scenarios.
- Forecasting; economics, population demography, lifestyles.
- Policy development; UNFCCC agreements, government targets and outcomes.
- Impacts; biophysical with human and natural environment responses.
- Re-alignment; feedbacks from impacts to economics, new policies and adjustments to existing states.

Of these, and despite associated uncertainties, it is perhaps the modelling of the climate that is the more reliable in terms of predictive ability using climate models and scenarios. In the

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[1] See: http://www.scottish.parliament.uk/s3/bills/17-ClimateChange/index.htm

[2] See: http://unfccc.int/files/meetings/cop_15/application/pdf/cop15_cph_auv.pdf

IPCC Fourth Assessment Report, Randall et al. (2007) state that '*there is considerable confidence that Atmospheric-Ocean General Circulation Models provide credible quantitative estimates of future climate change, particularly at continental and larger scales*'. It can thus be argued that projecting the future climate is somewhat more feasible than trying to envisage future economic and policy conditions, populations and human resource use. However, there remain considerable challenges in reducing uncertainty in climate modelling. From a physical systems point of view, the three main areas of uncertainty are: natural internal variability in the climatic system; emissions scenarios; and climate responses (i.e. Cox and Stephenson 2007). Of these it is generally recognised that in the short term, natural variability is more important, whilst in the long term this is replaced by model and emissions scenario uncertainty (Hawkins and Sutton 2009). To some extent this can be addressed by the use of multiple model ensembles (Murphy *et al.* 2004, Tebaldi and Knutti, 2007) and perturbed physics experiments (Murphy *et al.* 2007) to provide probabilistic ranges. For example Murphy *et al.* (2004) illustrate the range of global temperature increases possible form an ensemble of models versions (53) and different initialisations and parameter settings, giving probability density functions (5 – 95 % probability range) of 2.4 to 5.4°C.

Further challenges include the differences in the spatial scale of climate model coverage and the site specific nature of impacts and adaptation options, and how uncertainty in climate projections manifest themselves in other, secondary model based studies. These issues are key focal points covered in this thesis. For example,, studies of crop responses to climate change rarely quantify the uncertainty in either climate and crop model estimates (Challinor *et al.* 2009). Taking such a view, this study uses an IMF with data produced for a future climate scenario by the Hadley Centre's Regional Climate Model (HadRM3), as used for the UK climate projections 2002 (Hulme *et al.* 2002), to investigate the uncertainty in using climate and crop model estimates of impacts at the farm scale, so as to achieve a greater probability of viable adaptations to potential new biophysical conditions.

In researching how climate change (CC) will alter farm-scale agriculture in Scotland, and elsewhere, it is important to recognise the scope and limitations of what the research can consider. By its nature, an Integrated Assessment (IA) study will include a wide range of facets, each influencing on farm activities, and being either internal to the farm (soils, infrastructure resources, preferences etc.) or external (economics, policies etc.). This study focuses on the internal farm-scale aspects of how changes to the climate could manifest themselves, but takes a holistic over-view considering drivers of change at the national and international scales. A central theme to the study is the consideration of prediction uncertainty, with an emphasis on the evaluation of uncertainties in data quality and how introduced uncertainty can influence modelling based studies. What is not covered is the role that micro- and macro-economics play in determining the decisions made by farmers on the mixture of farm enterprises and their associated management. It has also been beyond the scope of this study to include full details on the crucial aspects of stakeholder evaluation of the process and outputs, and what adaptation actions would be undertaken given the information presented.

1.2 Aim.

The aim of the study was to explore the impacts of CC on farm-scale dynamics using a range of methods of differing levels of complexity and to examine the altered relationships between enterprises (arable, grass and livestock) within a farm. This would then allow transfer of findings to the wider context of agriculture and facilitate discussion on how adaptations could be made. The planned approach was to use an increasing level of complexity of model representation (Rivington *et al.* 2009b), starting at a ‘simple’ level using agro-meteorological metrics and progressing to the more complex cropping systems models and then finally a whole-farm integrated model. The focus would be on primary production (arable crops and grass) with the aspiration to include the impacts on livestock and subsequently the whole-farm dynamics. The extent to which the whole-farm model could be used would be tied to an objective within the study to develop new capabilities within the CropSyst cropping systems model (Stöckle *et al.* 2003) to represent perennial grass. This development would facilitate investigations into how grass production, and subsequently livestock systems, might change under a future climate. However, such an aim places a large risk resulting from failure to adequately develop CropSyst. As such a proviso was put in place that CropSyst could achieve a set of *a priori* evaluation criteria of grass production system representation in order for the livestock systems and therefore overall farm dynamics, to be investigated.

Indications of future climatic conditions and their impacts, especially if communicated in forms familiar to farmers and other land management stakeholders (commercial interests, policy makers etc.), will help inform them of critical thresholds of existing practises and potential for new ones in order to better prepare appropriate adaptation strategies (Matthews *et al.* 2008a). As such, this study aimed to utilise the concepts of resilience and adaptive capacity (Gunderson and Pritchard 2002, Holling and Gunderson 2002) to explore the potential for farming to meet the multiple objectives required of land use (such as food production, ecosystem services and environmental quality) whilst adapting to the biophysical (and policy and economic) changes. Resilience theory considers changes in the relationships between people and the environment which then enables a better understanding of how socio-ecological systems can adapt (see section 1.5.6 and Chapter 2 section 2.3). Adaptive capacity considers the 'scope' that a system (a mix of human and ecological, or 'socio-ecological system') has to maintain itself or retain its identity whilst transforming into an alternative form. Understanding the adaptive capacity of a socio-ecological system helps identify thresholds (or tolerance ranges) of a system in equilibrium under a given set of conditions (i.e. policy, economic, environmental) and therefore whether the thresholds are exceeded when perturbations occur (i.e. from climate change). The value of the resilience and adaptive capacity theory is in aiding decision making to maintain stability in socio-ecological systems during processes of transformational change. Whilst there are numerous drivers of change and influences affecting land management decision making, the main consideration is that a land manager will need to maintain financial viability. Hence within this study the emphasis is on the primary basis for income generation: productivity from the land uses within a farm.

1.3 Rationale.

By altering a significant component of the biophysical environment, future CC may require adaptations to land use and management. Such changes may be required to cope with both an increased incidence of extreme weather events and change in long-term mean conditions and variability. Despite adaptations of current management systems, more radical land use change, involving alterations to the mix of land uses and farm infrastructure may be required. Management systems adaptation to cope with the impacts of CC is, however, considered the most likely (Easterling 1996) whilst also holding the most promise for mitigation (Smith *et al.* 2007). Johnston and Chiotti (2000) are persuasive that decision-making is best studied at the whole-farm scale, which represents the interface between biophysical processes and human intervention through management. It is therefore necessary to understand how weather driven changes in the biophysical conditions within a farm determine the production capabilities within it.

It is also important to recognise the potential opportunities presented by an altered climate. Analysis of farm-scale management decisions in response to potential future conditions needs, however, to be given a wider socio-economic context, particularly through considering the influence of public policy measures, markets and supply-chains. Conversely, decisions at the farm-scale have important consequences for environmental protection and landscape quality that need to be considered at larger spatial scales. Fundamentally, the tolerances of what an area of land can support in terms of land use is primarily controlled by the biophysical constraints, of which the weather is the most important.

Global food security is becoming an increasingly serious concern, with an anticipated rise in human population to 9 billion by 2050 needing an increase of 70 % in agricultural production (FAO 2009). Hence there is need to better understand the production potential of cropping and livestock systems. Increasingly there will be need to balance multiple objectives: optimisation of production potential; requirements to maintain environmental quality; minimise greenhouse gas (GHG) emissions and maximise carbon sequestration (Robertson and Swinton 2005, Smith *et al.* 2007). In this respect it is necessary to consider agriculture at the global scale in order to place the Scottish case in context.

Given the wide range of potential consequences of CC it is valuable to explore alternative futures using simulation modelling. Counter-factual experiments within an IMF can be conducted to better understand the impacts of CC and the possible strategies for both mitigation and adaptation. Whilst the modelling focus of this study is at the farm-scale, it would be desirable to take a 'holistic' global perspective of the wider external influences on the implications of changes in agriculture and natural resource management, such as macro-economics and policies. This is also a requirement for the use of the resilience and adaptive capacity approach, as it is necessary to consider external influences to the socio-ecological system. However, as stated in section 1.1, it was not possible to include in this study the role of macro-economics. Instead, within conducting this research and presenting this thesis, it is recognised that macro-economics is most likely to be the key driver of change and adaptation. Whilst not quantified or incorporated within the specific components of this study, such a consideration is undertaken in presenting the conclusions. It is hoped that this research will contribute to the over-arching need to achieve sustainable farming systems.

1.4 Structure of Thesis.

This thesis is made up of 8 Chapters. This Chapter sets out the basis for the study and introduces the data, tools and concepts used. Chapter 2 covers the background to the study and forms a literature review of related research and seeks to place this study within the wider range of studies on climate change. Chapter 3 covers the issues of climate model uncertainty, particularly as they operate at spatial scales considerably greater than that at which farm-scale modelling studies are conducted. An evaluation is made of the Hadley Centre's HadRM3 Regional Climate Model and a simple bias correction downscaling method is detailed to enable the estimation of site-specific data for a future climate scenario. Chapter 4 looks at the issues of uncertainty and data quality in modelling based studies, with a particular focus on the role of weather data in influencing crop model estimates. The aim was to demonstrate the value of *a priori* evaluation and quantification of uncertainty in climate projections to increase credibility and hence utility of derived model estimates. In Chapter 5, details are provided of the use of agro-meteorological metrics to provide indications of future weather and soil conditions that influence farm management decisions. In Chapter 6 a cropping systems modelling approach is described and results given for the responses of spring barley and winter wheat to a future climate scenario compared against estimates derived from observed weather data. An evaluation of the CropSyst model's ability to represent grass systems is made in Chapter 7. The remaining content of the thesis would then be determined by the outcome of the CropSyst grass modelling evaluation. The final Chapter 8 forms a discussion of the findings, a critique of the approach and a brief set of conclusions.

This structure (see Fig. 1) represents a flow of process from model and uncertainty evaluation, uncertainty reduction, impacts modelling using a spectrum of model complexity (simple to complex), and synthesis into an overall discussion and conclusions.

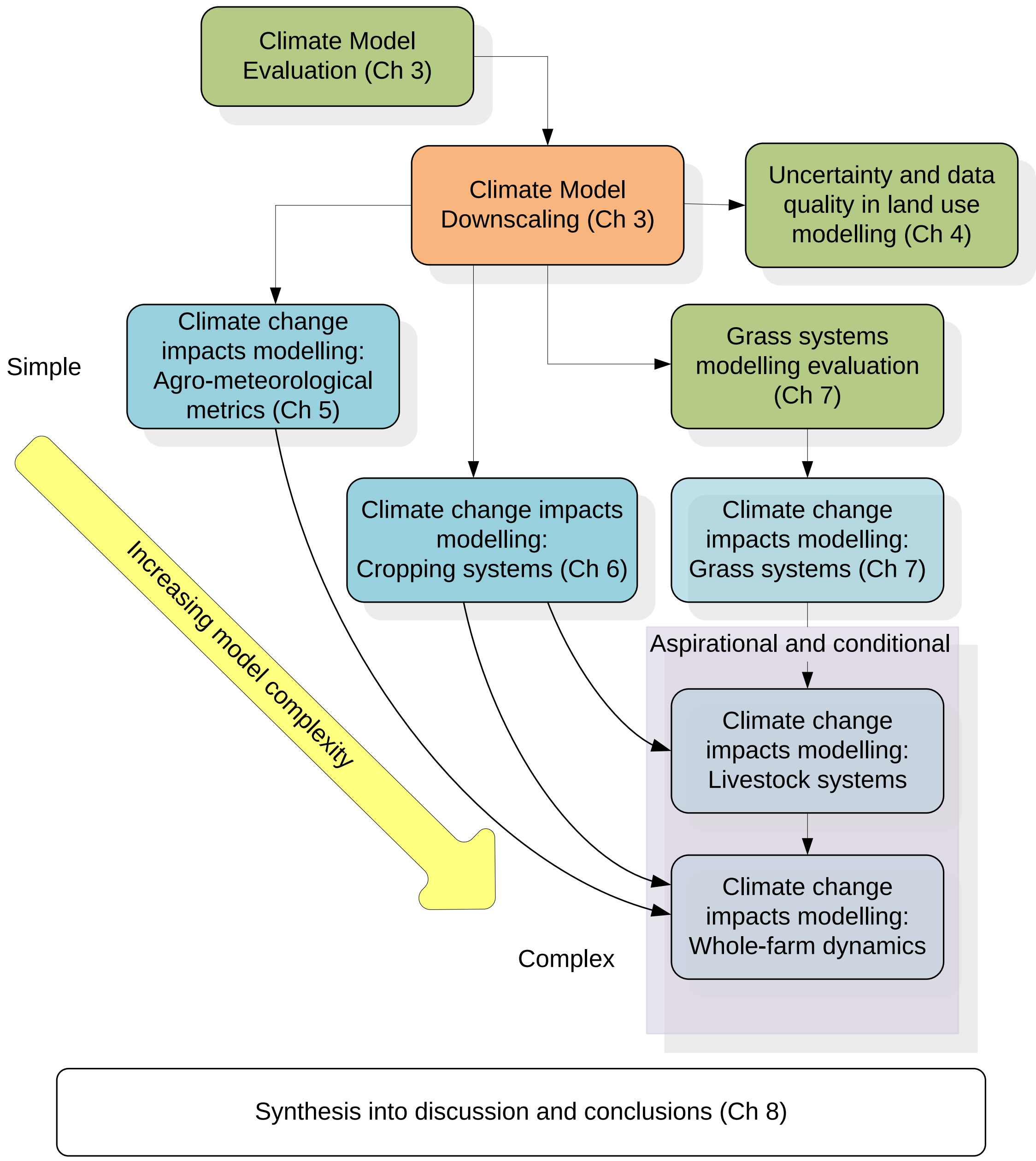

Figure 1. Schematic of work undertaken in this thesis. Research effort is divided into evaluation and uncertainty (green), uncertainty reduction (orange), climate change impacts modelling (blue). Areas in purple are aspirational and conditional on achievement of specified evaluation criteria.

1.5 Tools and concepts used in the study.

1.5.1 CropSyst.

CropSyst (Stöckle *et al.* 2003) is a multi-crop and multi-year daily time step crop growth simulation model. It was chosen for this study as it had previously been demonstrated to be a robust model capable of representing a wide range of cropping systems in many parts of the world, i.e. United Kingdom (Rivington *et al.* 2006b), Cameroon (Tingem *et al.* 2008, Tingem *et al.* 2009), United States (Pannkuk *et al.* 1998), France (Stöckle *et al.* 1997), Italy (Donatelli *et al.* 1997), Syria (Pala *et al.* 1996). Also, CropSyst has data requirements that can be reasonably met and provides support utilities to substitute for missing parameters based on well established procedures (e.g. using pedo-transfer functions to derive soil hydraulic parameters). It was also freely available for download and has supporting documentation, see:

http://www.bsyse.wsu.edu/CS_Suite/CropSyst/documentation/articles/description.html

Originally designed to represent arable crops, CropSyst's capabilities have been expanded to include a wider range of crops, include tea, grapes and other fruits. However, at the time of commencing this thesis, it did not have a specific capacity for representing grass systems. The model represents a number of physical, biological and management processes and interactions. It models soil water, crop-soil water and nitrogen budgets, crop phenology, canopy and root growth, yield and biomass production and organic residue decomposition.

CropSyst calculates biomass gain based on crop transpiration and transpiration-use efficiency, an approach that has been shown to be more robust than the radiation capture and radiation-use efficiency approach used by other models (Stöckle *et al.*, 2008). Estimating crop growth and yield as a function of water is particularly advantageous for applications in dryland regions, but may be less significant in locations where water is less limited.

However, this advantage may be beneficial when investigating the impacts of climate change, especially in respect of increased frequency and magnitude of dry spells.

Inputs to the model are daily weather data, soil and crop physiology parameters and management control parameters. The model requires daily precipitation, maximum (*Tmax*) and minimum (*Tmin*) temperature, and solar radiation (S_o). The accumulation of thermal time (growing degree days, GDD) controls crop phenological development to which the timing of management events can be tied.

The model allows the user to specify management parameters such as sowing date, cultivar genetic coefficients, soil profile properties (soil texture, thickness, water and initial nitrogen content), fertilizer and irrigation management, tillage, etc.. Crop growth is simulated for the whole canopy by calculating unstressed (potential) biomass based on crop potential transpiration and on crop intercepted photosynthetically active radiation. This potential growth is then corrected by any water and nitrogen limitations, to determine actual daily biomass gain. The simulated yield is then obtained as the ratio between actual total biomass accumulated at the time of harvest and a crop-specific harvest index (harvestable yield/above ground biomass). Water balance processes in CropSyst includes rainfall, runoff, and interception by the crop canopy and residues, infiltration, redistribution in the soil profile, crop transpiration and soil evaporation. Potential evaporation was estimated by the Priestley-Taylor method (Priestley and Taylor 1972) implemented within CropSyst. Water dynamics in the soil was handled by a Richard's equation; which is solved numerically using the finite difference technique.

Hence, it provides a conceptually unified modelling system for many crops, minimizing the dangers of structural uncertainty in making both cross crop and inter-spatial comparisons (Rivington *et al.* 2007). As such it is able to represent well the variation in yield determined by weather driven environmental conditions and respond to specific management regimen.

It has similar properties to the Decision Support System for Agro-technology Transfer (DSSAT) model (Jones 1986, see also: http://www.icasa.net/dssat/puborder.html), though is less detailed than the Agricultural Production Systems Simulator (APSIM) (Keating *et al.* 2003) and as such is less data and computer resource demanding. Each of these models (and others) have variations in representing crop growth, but they all utilise basic concepts of resource capture (in CropSyst's case light interception, water and nitrogen up-take), canopy structure and water use efficiency. Whilst CropSyst may be seen as being less detailed in process representation than models like the ones within DSSAT and APSIM, is generally regarded as being robust in its quality of estimates. However, there is little evidence of comparisons between CropSyst and other models. Exceptions include Clemente *et al.* (2005) who found that CropSyst estimated maize yield better than the CERES-Maize and SWACROP models under tropical conditions.

In order to develop grass modelling capabilities to satisfy requirements for this thesis, a process of collaboration with the developers at Washington State University was undertaken, whereby components were added and existing structures adapted to facilitate use of the model to estimate grass growth under a range of management regimen. These developments were critical in allowing linkages to be made between changes in grass production systems and the impacts on livestock systems and subsequently the use of the whole-farm model.

1.5.2 Agro-meteorological metrics.

Agro-meteorological metrics provide indications of environmental conditions on which land management decisions are made. Examples of metrics include the last day of spring air frost, the date of end of field capacity and the length of the growing season (see Table 9, Chapter 5). Metrics derived from observed weather data and an estimated future climate provide the opportunity to assess relative changes over time and to characterise the impacts of climate change on a wide range of land use practices (Rivington *et al.* 2008a). They are valuable tools in providing a form of representation of information that is easily understood by land managers (Matthews *et al.* 2008a) and facilitate discussion on potential adaptation measures (McCrum *et al.* 2009), whilst also serving as medium for communication between policy and practice (Rivington *et al.* 2009a).

1.5.3 Weather data.

This study used a common weather data source (detailed here to avoid repetition in each Chapter).

1.5.3.1 Observed weather data.

Daily observed precipitation (mm), maximum (*Tmax*) and minimum (*Tmin*) air temperature (ºC) and total downward surface shortwave flux (direct and diffuse solar radiation, S_o, MJ m^2 day^{-1}), or where available, sunshine duration (hours) data were provided by the British Atmospheric Data Centre (BADC: http://badc.nerc.ac.uk/home/index.html) for 24 sites in the UK (Fig. 2). The target time period for data use was 1960 to 1990, but this was not possible at all sites. Observed precipitation, *Tmax* and *Tmin*, and S_o (or sunshine duration) data were compiled within the Oracle database component of the IMF, where errors, duplicates and anomalies in the original data were identified and corrected during the database loading process. Missing observed values were filled using a search and optimisation method (LADSS 2005), though generally the data record was complete. However, observed solar radiation data is sparse, with three sites (see Fig 2.) not having any S_o data, whilst others had data for only part of the whole time period used. As alternatives where available, observed sunshine duration (hours) were converted to S_o using the Johnson-Woodward (JW) model (Rivington *et al.* 2005). When and where neither S_o or sunshine data were available, the Campbell-Donatelli method (CD) was used to convert observed air temperature to S_o values (Donatelli and Campbell 1998, Rivington *et al.* 2005).

1.5.3.2 Modelled weather data.

Modelled climate data used in this study originates from the Hadley Centre's HadRM3 RCM archive for 50×50 km grid cells (the extent of each RCM cell used is shown in Fig. 3), being part of the data set used to produce the 2002 Climate Change Scenarios for the United Kingdom (Hulme *et al.* 2002). As an initial condition ensemble, five hindcast simulations (starting from 1860) were produced by the HadRM3 in order to establish 1960-90 climate normal period 'baselines' to be used for comparisons with future projections. Each hindcast simulation had slight variations in their initialisation conditions, but atmospheric CO_2 and other GHG concentrations were varied to match the historical concentrations up until 1990. Future projections of GHGs, as per the Special Report on Emissions Scenarios (SRES) (IPCC 2000, Arnell *et al.* 2004) were not applied until after 1990. This paper uses the SRES A2 (medium-high GHG emissions) initial realisation hindcast (based on observed historical GHG concentrations). As such, this paper assesses and uses only one example of the hindcast configurations of the HadRM3.

The hindcast data produced by the RCM do not attempt to recreate synoptic conditions for specific locations or years. Instead they aim to provide a time-series of data with the correct statistical properties including correlations between variables. The RCM outputs represent the 50×50 km grid cell as a whole rather than any specific site within the cell and are time (year) independent. Therefore direct day-to-day or year-with-year comparisons between the observed and RCM data are not possible. Instead, mean daily, annual totals or maximum and minimum values were used for comparisons. As the HadRM3 model treats a year as having 360 days (i.e. twelve months of 30 days), the last five days of the observed data for each year were omitted from the analyses, though this risks the exclusion of significant extreme weather events in this time.

1.5.4 Locations.

A total of 24 sites in the UK were used for one, several or all of the following: Regional Climate Model evaluation and downscaling; agro-meteorological metrics application; crop model uncertainty evaluation; and crop modelling of future productivity. The sites are shown in Figure 2. These sites were chosen as they had data records of the required variables (precipitation, maximum and minimum temperature, and either solar radiation or sunshine duration), and for time periods that included, as well as possible, the climate normal period of 1960 to 1990.

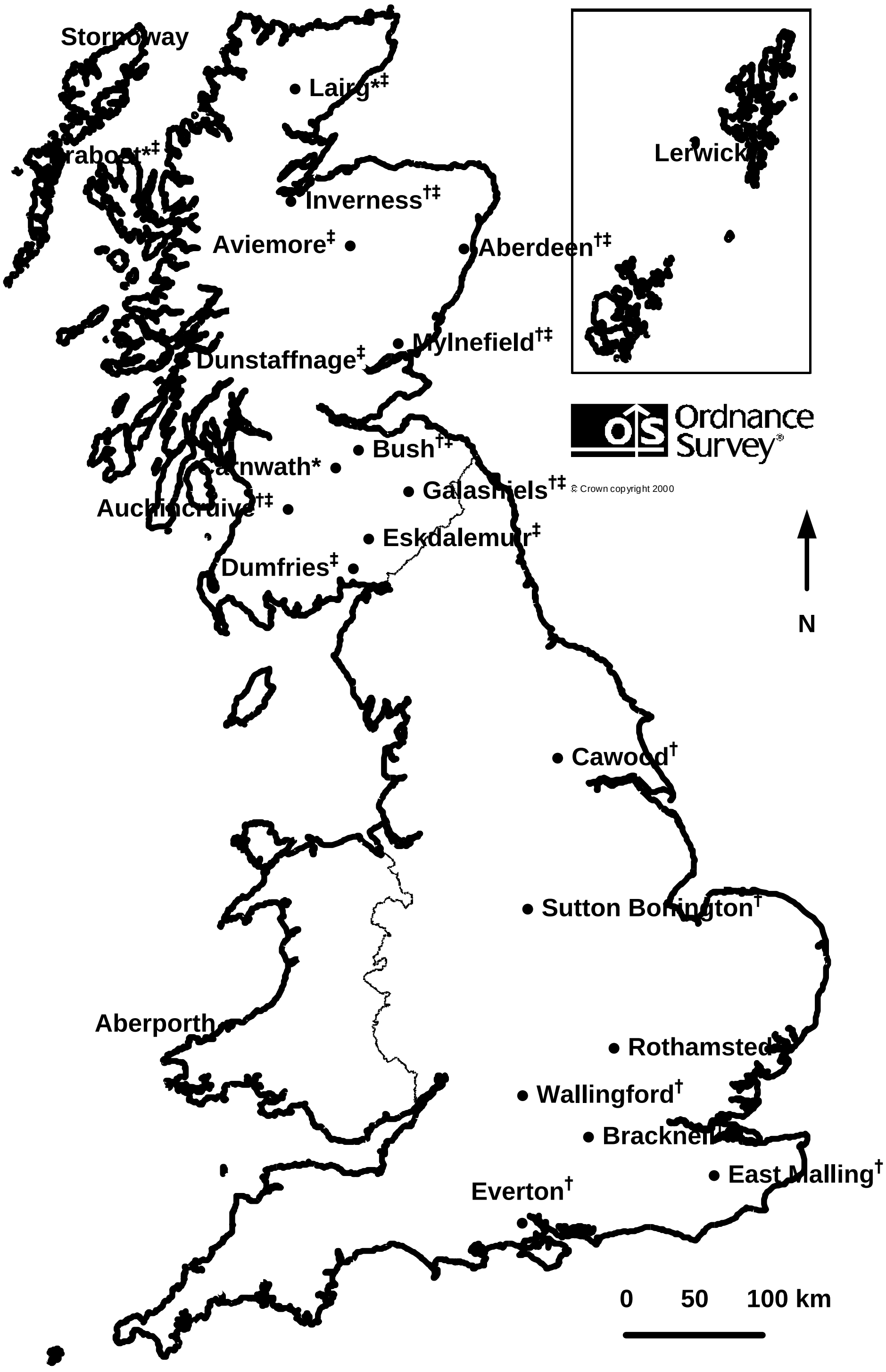

Figure 2. Locations of sites used within the study. * Sites without observed solar radiation (S_o). † Sites used for Chapter 4. ‡ Sites used for Chapter 5.
NB, Aldergrove in Northern Ireland is not shown

1.5.5 Integrated Modelling Framework.

Conditional on CropSyst achieving satisfactory performance in simulating grass systems, this study aimed to utilise the biophysical whole-farm modelling capabilities that form part of an IMF approach (Rivington *et al.* 2007). At the core of this framework is the Land Allocation Decision Support System (LADSS) (Matthews *et al.* 1999). The aim was to utilise the agro-metrics and CropSyst to add detail to the future scenario by characterising the changes in the biophysical environment and produce estimates of changes in crop, grass and livestock production, as well as of the processes and inter-relationships with management that enable production. This information would then be fed into the LADSS tool to compile into a single farm model to enable counter-factual assessment of changes in the land use mix within the farm and to evaluate the changes in the dynamics of management requirements. The capacity to do this would be highly dependent on successfully developing the CropSyst model to represent grass production systems, as this is an essential part of providing information relevant to the livestock systems modelling component.

The core of LADSS is made up of biophysical and management systems' models, of which CropSyst is one. These are primarily driven by farm-scale biophysical and management regimen data, though they also reference meso- and macro-scale data such as market prices for inputs and sales. The accounting framework defines views on the state variables of the system being simulated. The accounting framework thus presents a coherent and organised view of the state information, such as financial (gross/net margins or cash flow) or physical accounting (nitrogen balance or net greenhouse gas emissions). Beyond the accounting framework are supporting tools for analysis, including multi-objective land use planning, cost-benefit analysis or sustainability assessment. As such LADSS represents the 'complex' end of the model complexity spectrum, with correspondingly higher data requirements, skill in parameterisation and operation, and capacity for validation (i.e. Bellocchi *et al.* 2009)

The extent to which integration of modelling capabilities can be achieved is to a large extent determined by the quality of estimates made by individual component models within the framework. Estimate errors made by any one component model can be propagated through to the overall farm-scale model, hence distorting outputs. Hence there is interdependence on achieving adequate estimate quality across all models within the framework.

The biophysical systems' models within the framework are CropSyst (Stöckle *et al.*, 2003) and a bespoke livestock systems model (LSM) (Matthews *et al.* 2006a). CropSyst was chosen from a review of alternative crop models since it provides a conceptually unified modelling system for many crops minimising the dangers of structural uncertainty in making cross crop comparisons. Novel crops, i.e. bio-fuels or genetically modified crops can be modelled, where parameterisation is possible, permitting exploration of alternative forms of land use. The LSM is an energetics based livestock growth model that tracks the state of cohorts of ruminants, as they progress from birth through weaning and growth to finishing for market. The definition of the herds through which cohorts progress, the linkages between herds and the management decisions required are implemented using a graphical programming toolkit. Intake requirements for specified diet are estimated for each cohort and stocking rates set to be consistent with materials available in a fodder pool, that is made up of on-farm (modelled within CropSyst) and bought in materials. The interactions between grazing stock and pastures can be simulated using daily clipping events whose magnitude is set by the LSM. Such close linkages between the LSM and CropSyt was a further objective of this thesis. The viability of this linkage is dependent on the ability of CropSyst to represent a range of grass production systems (silage conservation, grazing by sheep and / or cattle, or mixed silage and grazing).

The quality of analyses depends on the quality of farm and meso/macro-scale input data, but the biophysical and management systems' models were chosen, if not to minimise data requirements, then to depend on a small number of relatively easily measured parameters. Whilst the framework is robust in the face of missing data with the ability to substitute either experiential or standard published figures, the response to unknowns arising from climate change places an additional reliance on component modelling capabilities. This does, however, clearly restrict the range of analyses possible. The models are, where possible, calibrated and validated against on-site data. Un-calibrated or non-validated outputs are flagged and used only as indicative of trends.

The management systems model within the IMF is the resources scheduling tool (RST) (Matthews *et al.*, 2003). The RST is a heuristic based scheduler that determines the utilisation of on-farm resources such as labour and machinery, based on tasks generated from patterns of land use and the livestock management regimen. The RST can also assign machinery intensive or specialist tasks to contractors where appropriate. The outputs from the RST are used in determining the fixed costs for patterns of land use and management. The IMF also has deliberative support aspects which are higher-level tools that make use of the functionality provided by the biophysical and management systems' models and the accounting framework. These tools support the deliberative process by presenting in a structured way a range of options to decision makers or stakeholders. These serve as marketing planning tools, defining a set of alternative states with estimated properties.

The options presented may serve as the basis for plans with further customisation by decision makers to reflect their preferences or factors not considered by the tools, or can be used as part of an iterative process of evaluation.

The tools developed to date have focused on spatial allocation problems and finding patterns of land use that achieve the best possible balance between multiple objectives. The outputs from these tools are typically a set of Pareto-optimal solutions (where an optimum is found between opposing objectives) that define the trade-off between objectives (Matthews *et al.* 1999). Pareto-optimal solutions are estimates of the best mix of options to achieve multiple objectives, i.e. profitability and land use mix diversity (or risk avoidance), and are the closest possible to an ideal solution without entering into infeasible (or mutually exclusive) combinations.

Whilst the IMF can consider a wide range of environmental and policy consequences it is not comprehensive. It is not yet possible to assess animal welfare and consequential labour requirements, crop quality with its implications for market value or feed for livestock, nor the potential impacts on the prevalence of pests and diseases in both plants and animals. Such omissions may, however, be considered qualitatively through the deliberative process. Structurally the IMF has limitations on the degree of integration between its sub-systems. For example, it is not possible to adaptively adjust stocking rates in response to grazing availability within a single simulation of pasture growth. This can be significant as the grazed pasture's growth is a function both of agro-climatic conditions and the imposed grazing regimen. The grazing regimen determined by the LSM defines one of the management parameters for the CropSyst simulation. Any adjustments to the grazing regimen must be made at the completion of a CropSyst run using the diagnostics provided and a further CropSyst simulation made. A further limitation of the IMF is that while simulations are spatially explicit, in that they are conducted on a field-by-field basis, the component models are not distributed and thus cannot take account of lateral flows (which can be significant for soil-water regimens) or changes in the influences of surrounding fields (such as shading or shelter) during the course of a simulation.

1.5.6 Resilience and adaptive capacity framework.

Given the wide range of analyses possible within CC impact assessment it is useful to set the analysis in the context of a conceptual framework that can serve to underpin, organise and assist in interpreting the outcomes of the research. One such framework is based on resilience and adaptive capacity. Chapter 2 gives a further overview of resilience and adaptive capacity. Here it is worth noting that Easterling (1996) contrasts short-term system resilience with long-term adaptive capacity. A system with short-term resilience can adapt its operations to maintain existing functionality, absorbing impacts of varying magnitudes.

Systems with long-term adaptive capacity are able to manage the process of altering their operations, function and appearance to continue to deliver higher-level goals such as food supply or income for land managers, and landscape value. Thus adaptive capacity is required when change exceeds the short-term resilience of the system, but must seek to maintain long-term resilience without degrading system functions or reducing capital value (social, natural, human, financial and built / infrastructure).

Hence identification of the limits on a farming system's resilience, the capacity to increase that resilience via changes to management systems and the consequences of such changes, make useful contributions to the assessment of CC impacts, especially within an Integrated Assessment study. The assessment of farming system's long-term adaptive capacity in the face of CC, however, makes a more significant contribution to the wider debate on the long term sustainability of land use systems. In this study the resilience and adaptive capacity concept is used to structure the findings, and evaluated in terms of its utility for these purposes.

1.6 Summary of aims and objectives.

- Explore the impacts of climate change on farm-scale dynamics in a Scottish context.
- Evaluate main modelling tools and data to better understand uncertainty: climate model estimates, impacts on land use system model estimates.
- Develop grass modelling capabilities and evaluate based on *a priori* criteria.
- Use a range of modelling tools and understanding of uncertainty to explore climate change impacts on: bio-climatic conditions (agro-meteorological metrics), cropping and grass systems (CropSyst).
- Conditional on achieving a satisfactory level of grass production system representation, model climate change impacts on livestock systems.

- Compile findings within a holistic modelling framework and utilise the concepts of resilience and adaptive capacity to explore the inter-relational aspects of impacts and potential adaptation options.

Chapter 2: Background and related research.

2.1 Introduction.

The need for adaptation to change is a permanent feature of management decision making when working within the constraints of natural systems, with farming being no exception. The requirements for adaptation are extending beyond traditional considerations of weather variability, market conditions and government policies to now include the requirements driven by climate change. Influences on decision making include alterations to farming practices for both mitigation to reduce greenhouse gas emissions, and to cope with the changes in biophysical conditions under a new climatic state and pattern of weather variability. Beyond this (on a global scale but related to farm scale practises) there is also a need to include a widening range of multiple objectives for land use, i.e. biodiversity, ecosystem services, climate regulation and poverty alleviation (Munang *et al.* 2010). There is now an aim of limiting global warming to 2°C above pre-industrial levels (IPCC 2007c, UNFCCC 'Copenhagen Accord'[3]). Planning strategies to enhance the probability of achieving these multiple objectives (i.e. when looking at the farm scale), thus have to evaluate the trade-offs between individual objectives (which may be either limited in their complementarity, or are incompatible). Subsequently there is need to establish particular priorities for the objectives and recognise the nature and scale of the multiple drivers of change that determine the responses of the components that make up a farm's system.

Given the difficulties in making projections of future economic and policy conditions, at both local and global spatial scales, there is potentially greater gain in estimating the

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[3] See: http://unfccc.int/resource/docs/2009/cop15/eng/11a01.pdf

probable impacts of climate change on the biophysical components influencing farm-scale decision making. In terms of adaptation planning, an issue thus arises as to the reliability and utility of future climate projections. Quantifying the uncertainty in future climate projections serves to aid decision making for adaptation by indicating the range and probabilities of possible impacts and helps understand the behaviour of individual entities and processes within complex systems. However, adaptation strategies should not be constrained by the accuracy and precision of climate projections, instead there is need for robust and flexible decision making (i.e. Dessai *et al*. 2008) to allow for a range of plausible climate futures.

This Chapter provides a review of the research areas making up the suite of approaches used in this study.

2.2 Climate change impacts.

It is important to distinguish two types of climate change impacts: those resulting directly from changes in the climate (physical and biological), and those based on societal level responses (either to mitigate against, or adapt to climate change) and how they manifest themselves within economics and policies. This distinction initially allows the separation of research into the two types, but ultimately there is a need for a research strategy that allows both types to be integrated, as there are vital cause and effect inter-linkages between the two. There are also differences in the timescales in which the two types of impacts occur: the changes in climate may be slow and gradual, covering centuries to decades (IPCC 2007b); whilst new policies and economic mechanisms can emerge over relatively short time periods (i.e. the UNFCCC Kyoto Protocol, the Climate Change (Scotland) Act 2009). In a time sequence, people in developed countries are generally more likely to feel the effect of changes in policies and economics before those of the climate. The opposite is probable for those in developing countries, having consequences for trade in food products (Nellerman *et al.* 2009).

2.2.1 Global to local scale climate change.

2.2.1.1 Global.

At the global scale, the mean temperature has risen by about 0.74°C between 1906 and 2005, though there are large regional variations (Trenberth *et al.* 2007). Projections of further increases vary with economic and GHG emissions scenarios and climate modelling approaches used. The IPCC climate and economic scenario A1Fl (UKCIP02 'High emissions', Hulme *et al.* 2002) from the Special Report on Emissions Scenarios (SRES) (Nakocenovic and Swart 2000) gives a multiple model projected mean surface air temperature (SAT) rise of +3.97°C (with uncertainty ranges of +2.4°C to +6.4°C) for the period 2090-99 above the 1980-1999 period (mean SAT of 13.6°C), though this is based on modelling with limited feedback mechanisms (IPCC 2007b). Current emissions rates are on a similar trajectory to the A1Fl scenario (fossil fuel intensive), having grown from 1.33% increase per year in the 1990's to 3.3% in the period 2000 to 2006 (Canadell *et al.* 2007). For other SRES emissions scenarios, the IPCC (2007b) reported global mean warming for time slices (2011-2030 and 2046-2065) for the multiple model mean SAT for 2090-2099 relative to 1980-1999 (with ranges):

- B1 (UKCIP02 'Low emissions'):
    - 2011-2030 = +0.66°C (+/- 0.05°C)
    - 2046-2065 = 1.29°C,
    - 2090-2099 = +1.8°C (1.1°C to 2.9°C)
- B2 (UKCIP02 'Medium-Low emissions'):
    - 2090-2099 = +2.4°C (1.4°C to 3.8°C)
- A1B:

- 2011-2030 = +0.69°C (+/- 0.05°C)
- 2046-2065 = +1.75°C
- 2090-2099 = +2.8°C (1.7°C to 4.4°C)

- A1T:
  - 2090-2099 = +2.4°C (1.4°C to 3.8°C)
- A2 (UKCIP02 'Medium-High emissions'):
  - 2011-2030 = +0.64°C (+/- 0.05°C)
  - 2046-2065 = +1.65°C
  - 2090-2099 = +3.4°C (2.0°C to 5.4°C)

As stated in section 1.1, uncertainties in the global projections arise from multiple sources. In terms of quantifying the ranges of uncertainties in climate projections as provided above, the IPCC Fourth Assessment Report utilised climate models operating at different levels of spatial, temporal and process representation complexity.

The IPCC (2007b) report also estimated, even without additional emissions, that there is a committed warming of c. 0.1°C per decade for the next two decades, with the rate declining afterwards.

The range and magnitude of impacts across the globe are many and variable but can be summarised as (relative to land use and agriculture) (IPCC 2007a):

- Changes in rainfall amounts and seasonal distribution.
- Increasing temperatures with associated impacts on evapotranspiration (Jung *et al.* 2010).
- Decreasing water availability and increasing drought in mid latitudes and semi-arid low latitudes (increased evaporation and subsequent decrease in soil moisture), but increasing water availability in the tropics and high latitudes. Changing levels of

availability of water from snow melt affecting approximately 1/6th of the global population (Barnett *et al.* 2005).

- Increase in the frequency of extreme events (droughts, heat waves, flooding), with storms of higher intensity (Mitchell *et al.* 2006).
- Decreasing yields in tropical and mid latitudes (with associated increase in yield variability), but potentially increasing in high latitudes (Tan and Shibasaki 2003).
- Major losses of biodiversity and extinction (Thomas *et al.* 2004).
- Increase in human and animal diseases and decline in health.

2.2.1.2 Europe.

Changes at the European level will have a significant impact on Scottish agriculture through alterations of the regions' ability to produce food and consequences on markets. According to the IPCC fourth Assessment Report (IPCC 2007a), across a range of emissions scenarios, annual mean temperatures in Europe are likely to increase more than the global mean. As with the global projections, there are large variations between simulations of temperature and precipitation change for each model and scenario combination (Ruosteenoja *et al.* 2003). These authors produces scatter diagrams of precipitation (%) and temperature change based on unforced 1000 year AOGCM simulations to create seasonal (3 months) baselines and seven different GCMs projections for the four main SRES scenarios for future time slices for 39 regions in the world. These diagrams illustrate the variation in projections, for example in Northern Europe for December to February 2040-2069 time slice there is a precipitation change range from near zero to +40% and temperature change from approximately 2°C to 8°C. For the same time slice, the models show much less variation (less scattering) for the June to August period. All seven models were consistent in projecting precipitation and temperatures that were outside of the 95% Gaussian contour ellipses representing the baseline natural variability. Taking into consideration such large variations in model

estimates, the Fourth Assessment Report (IPCC 2007a) concluded that seasonally, warming is not going to be geographically even with the largest warming likely to be in northern Europe in winter and in the Mediterranean area in summer. Minimum winter temperatures are likely to increase more than the average in northern Europe. Maximum summer temperatures are likely to increase more than the average in southern and central Europe.
Changes to the hydrological cycle in Europe indicate a divergence between southern and northern areas (IPCC 2007a, Falloon and Betts 2010). Annual precipitation is very likely to increase in most of northern Europe and decrease in most of the Mediterranean area. In central Europe, precipitation is likely to increase in winter but decrease in summer. This is likely to increase the demand for water in the summer, particularly for crop irrigation. The extremes of daily precipitation are very likely to increase in northern Europe, whilst the annual number of precipitation days is very likely to decrease in the Mediterranean area. The risk of summer drought is likely to increase in central Europe and in the Mediterranean area. The duration of the snow season is very likely to shorten, and snow depth is likely to decrease in most of Europe, with consequences for river flow.

Though such changes may present new opportunities for agriculture in northern Europe (new crops and rotations, expansion of cultivated areas) there are also disadvantages arising from the need for greater plant protection (weed, pest and pathogen control), loss of nutrients and increased turnover of soil organic matter. The overall balance of benefits and disadvantages may reinforce the current trend of agricultural intensification in northern and western Europe, and extensification in the Mediterranean and south-eastern areas (Olesen and Bindi 2002, Supit *et al.* 2010). These changes are also reflected in changes to ecosystem services in Europe, both in terms of functions and risk levels, as climate impacts (and associated policies and economic responses) affects land use change. Such changes could be positive in some areas in terms of increased biomass production and additional land suitable for agriculture, but also negative due to reduced water availability and soil fertility, also with an increased risk of forest fires (Schröter et al. 2005).

Such changes also have to be put into context with other drivers of change, including the balance between potential increased productivity (due to the benefits of elevated CO_2, climate change and technological advances) and reduced demand in Europe and effect on regional competitiveness and allocation of land for agricultural purposes (Hermans *et al.* 2010). The potential variation in production and competitiveness detailed by these authors reflects the potential changes at a global scale (Tan and Shibasaki 2003, IPCC 2007a), highlighting the complexity of multiple, primarily economic driven, interactions between regions. A key to the outcome of these multiple interactions between regions may be the combination of the adaptation responses by farmers and the phasing of climate change impacts, e.g. one region suffering extreme weather impacts and reduced agricultural productivity whilst another has beneficial conditions. Such regional variations are likely to require trade agreements that ensure stability of supply and legislation that ensures environmental protection. The potential impacts arising from climate change therefore need to be placed within a context of adaptation by land managers to the mix of influencing factors, of which climate change is just one.

2.2.1.3 United Kingdom.

The following is a summary from Jenkins *et al.* (2007) and Barnett *et al.* (2006) on recent trends in the UK. The Central England Temperature (CET) is the longest instrumental record in the world, with mean monthly (from 1659) and daily (from 1722) air temperature data covering the Midlands region of England (Manley 1974, UK Met Office 2010). It has risen by about 1°C since the 1970's, with 2006 being the warmest on record (dating back to 1659). The mean annual CET in 2006 was 10.82 °C, being 1.35 ± 0.18 °C above the mean for the 1960-1990 period. In Scotland the mean annual temperature increased by 1.0 °C between

1961 to 2004 (0.5% between 1914 to 2004), with the greatest warming occurring over the winter (1.22 °C). Mean annual precipitation has not changed significantly over England and Wales. In Scotland there was a 21% increase in mean annual precipitation between 1961 to 2004 (6.2 % between 1914 to 2004). There was a marked difference between summer (0.6% decrease) and winter rainfall (58% increase). In Scotland, only the northern area has there been a significant trend for sunshine duration (13.8% decrease in the winter, annual amount had a 5.6% decrease, both between 1929 to 2004).

Projections for a future climate in the UK vary with modelling approach used, location, emissions scenarios and time period considered. Hulme *et al.* (2002) reported that annual warming rates could be between 0.3°C and 0.5° per decade for the high emissions SRES scenario (IPCC 2000), giving a range of 2 to 3.5°C warming range for average annual temperature across the whole UK, depending on scenario, the 2080s period. More warming was projected to occur in the southeast than the northwest, as well as in the summer and autumn than in the winter and spring. For the high emissions scenario, the south-east of England may be 5°C warmer by the 2080s. For precipitation, Hulme *et al.* (2002) reported projections showing wetter winters (up to 30% for some locations and scenarios), and also drier summers (up to 50% for some locations and scenarios), but little change in the annual total.

The projections detailed in Hulme *et al.* (2002) were superseded by the UKCP09 projections[4], presented as probabilitistic estimates based on a large climate model ensemble (Murphy et al. 2009) (but released too late for use in this study). The projections for the UK can be summarised by the 2080s period as:

Precipitation change (%) for mean annual (a), mean winter (w), mean summer (s) (10th, 50th and 90th percentiles per scenario):

- High emissions:

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[4] Released in June 2009. See: http://ukclimateprojections.defra.gov.uk/content/view/868/531/

- Highest change; a) -3, +3, +20; w) +18, +47, +97; s) -8, 0, +10.
- Lowest change; a) -21, +6, +3; w) -12, -3, +6; s) -74, -49, -10.

- Medium emission:
  - Highest change; a) -3, +2, +14; w) +9, +33, +70; s) -8, +1, +10.
  - Lowest change; a) -16, -3, +3; w) -11, -2, +7; s) -65, -40,-6.

This indicates that for the high emissions scenario and the highest change, the range of winter precipitation is not likely to increase less than 18% and unlikely to be more than 97%, with the mid (50^{th} percentile) being a 47% increase. For the lowest change, winter precipitation in unlikely to decrease by more than 12% or increase by more than 6%. The probability range for annual and summer are somewhat smaller.

Temperature change (°C) for daily mean winter (w), summer (s), daily maximum winter ($Tmax_w$) and summer ($Tmax_s$) daily minimum winter ($Tmin_w$) and summer ($Tmin_s$) (10^{th}, 50^{th} and 90^{th} percentiles per scenario):

- High emissions:
  - Highest change; w) 2.2, 3.8, 5.8; s) 2.9, 5.3, 8.4
    - $Tmax_w$ 1.6, 3.4, 6.1; $Tmax_s$ 3.0, 6.8, 11.7
    - $Tmin_w$ 2.0, 4.2, 7.0; $Tmin_s$ 2.8, 5.3, 8.8
  - Lowest change; w) 1.0, 2.1, 3.5; s) 1.6, 3.1, 5.0
    - $Tmax_w$ 1.1, 2.3, 3.9; $Tmax_s$ 1.2, 3.5, 6.3
    - $Tmin_w$ 0.8, 2.4, 4.3; $Tmin_s$ 1.7, 3.3, 5.6
- Medium emission:
  - Highest change; w) 1.7, 3.1, 4.8; s) 2.2, 4.2, 6.8
    - $Tmax_w$ 1.3, 2.9, 5.1; $Tmax_s$ 2.2, 5.4, 9.5
    - $Tmin_w$ 1.5, 3.5, 5.9; $Tmin_s$ 2.0, 4.1, 7.1
  - Lowest change; w) 0.8, 1.8, 3.1; s) 1.2, 2.5, 4.1

- $Tmax_w$ 0.8, 2.0, 3.4; $Tmax_s$ 1.1, 2.8, 5.0
- $Tmin_w$ 0.6, 2.1, 3.7; $Tmin_s$ 1.3, 2.7, 4.5

Under the High emissions scenario for the highest change, the range of mean daily summer temperature is not likely to increase less than 2.9°C and unlikely to be more than 8.4°C, with the mid (50th percentile) being a 5.3°C increase. For the lowest change, summer daily mean temperature is not likely to increase less than 1.6°C or be more than 5.0°C, with a mid range estimate of 3.1°C (this value corresponds closely to the high emissions estimate for mean temperature increase from the UKCIP02 projections reported in Hulme *et al.* 2002).

For Scotland, the UKCP09 projections can be summarised as:

Precipitation change (%) mean annual (a), winter (w) and summer (s) (10th, 50th and 90th percentiles for the medium emissions scenario by the 2050s period);

- North Scotland; a) –6, 0, +5; w) +3, +13, +24; s) –23, –10, +2
- East Scotland; a) –4, 0, +5; w) +2, +10, +20; s) –26, –12, +1
- West Scotland; a) –6, 0, +5; w) +5, +15, +28; s) –26 –12 +1

This can be compared against:

- South East England; a) –4, 0, +6; w) +2, +16, +36; s) –40, –18, +7

Temperature change (°C) for mean winter (w) summer (s), mean daily maximum summer ($Tmax_s$) and mean daily minimum summer ($Tmin_s$) (10th, 50th and 90th percentiles for the medium emissions scenario by the 2050s period);

- North Scotland; w) 0.6, 1.7, 2.8; s) 0.9, 2.0, 3.4
    - $Tmax_s$ 0.8, 2.5, 4.5; $Tmin_s$ 0.9, 2.3, 3.9
- East Scotland; w) 0.7, 1.7, 2.9; s) 1.1, 2.3, 3.9
    - $Tmax_s$ 1.0, 3.0, 5.4; $Tmin_s$ 1.1, 2.5, 4.3
- West Scotland; w) 1.0, 1.9, 3.0; s) 1.1, 2.4, 3.8
    - $Tmax_s$ 0.9, 3.0, 5.2; $Tmin_s$ 0.9, 2.4, 4.2

This can be compared against:

- South East England; w) 1.1, 2.2, 3.4; s) 1.3, 2.7, 4.6
    - $Tmax_s$ 1.4, 3.7, 6.5; $Tmin_s$ 1.3, 2.9, 5.1

Whilst there is evidence that agriculture in the UK has adapted in the past to extreme climatic events, reducing the amount of damage caused, it is questionable as to how much further adaptation can develop without an increase in productivity loss (Wreford and Adger 2010). However, there is a potential lack of awareness of climate change issues in UK agriculture, meaning it may not be well prepared for future impacts (Tate *et al.* 2010) despite the opportunities due to there being a probable reduction in the climatic constraints (Brown et al. 2008). How changes in the climate manifest themselves in terms of impacts on agriculture in the UK is likely to vary geographically and in response to the mixture of policies, economics and adaptations undertaken by land managers.

A key point from the above is that in considering climate change impacts, there are wide variations in their spatial and temporal scales. These arise from differences in *modelling*, *representation* and *scenario* uncertainty which are discussed later.

2.3 Resilience and adaptive capacity.

Given the uncertainty in future climate projections and range of potential impacts, it becomes necessary to understand and quantify the nature of impacts and uncertainty to better assess how resilient a farm may be. The next section explores the concept of resilience and adaptive capacity in order to assess its suitability as a framework that can serve to underpin, organise and assist in interpreting the various forms of estimates made within this study.

Resilience can be defined as '*the capacity of a system to absorb disturbance and reorganize while undergoing change so as to still retain essentially the same function, structure and* *feedbacks - and therefore the same identity*' (Resilience Alliance, http://www.resalliance.org/). Resilience theory (Holling and Gunderson 2002) is concerned with understanding the details of the change in respect of relationships between people and the environment. It suggests that a system can move between one stable state to another (each of which can be stable) and have the same identity (i.e. an arable farm can change the composition of its individual land uses, management and labour resources etc. over time, but still remains an arable farm).

The context of studies on resilience and adaptive capacity is that of socio-ecological systems (SES) and the provision of ecosystem goods and services (food, water, climate regulation, health provisions etc.). The Resilience Alliance (http://www.resalliance.org/1.php) defines an SES as "*a multi-scale pattern of resource use around which humans have organized themselves in a particular social structure (distribution of people, resource management, consumption patterns, and associated norms and rules)*". This implies that the spatial focus of this thesis, the farm-scale, exists as several spatial levels (plant / animal to field to farm) within an SES made up of many more scales (particularly large ones related to economics and policy). Defining the 'farm' within such a multi-scale pattern and being in a particular phase thus becomes problematical, as the 'state and phase' can be site (climatic, soil, topography etc.) and owner / manager (preferences, skills, objectives) specific.

If a re-working of the definition of resilience is taken as the maximum disturbance a system can take and then return to the same equilibrium (i.e. Folke *et al.* 2002), then the question has to be asked 'what is a desirable equilibrium?'. This implies having a goal and clear image for the state that the system exists in and can change to. Here it is necessary to consider again the multiple drivers of change and multiple objectives for land use (both at the farm and landscape scale, within a global context) and the need for trade-offs between objectives. In this respect resilience theory utilises the concepts of cross scale interactions (to address multiple drivers of change) and adaptive change and learning. However, climate change imposes new drivers of change (i.e. GHG mitigation requirements) and altered biophysical properties (i.e. soil moisture balances), hence an equilibrium based on a stable state under previous economic, policy and biophysical conditions may not be appropriate under future conditions.

Whilst from a farm business perspective, the essential bottom line is to maintain financial viability, there is also need to balance the need for ecosystem services provided at the farm and landscape scale. Hence a farm manager needs to understand the cross-scale interactions (primarily of the economic conditions and constraints of policy in determining management strategies), whilst their ability to learn and adapt is dependent on many factors. These include personal preferences and choices influenced by social capital (Nelson *et al.* 2007) and experience, biophysical (soils, climate, i.e. Brown *et al.* 2008) and financial constraints (savings, terms of bank loans etc.).

Folke *et al.* (2002) argue that management can destroy or build resilience, depending on how the SES organises itself in response to the management actions. On the basis that more resilient SES are able to absorb larger shocks and that when transformations do occur, resilient systems have the essential attributes and properties needed for renewal and re-organisation, a management goal may be to build resilience. It therefore becomes essential to understand what constraints there are on management interventions, for example due to restrictions imposed by policy or biophysical limitations, but also where opportunities may arise.

A further concept within resilience theory is that of adaptive cycles (Holling 1995, Allison and Hobbs 2004), which attempts to understand the processes of change within complex systems. The basis is that a system is in a permanent process of flow through time through four different phases (exploitation, conservation, release and reorganisation) of an ecosystem to form a cycle, which is related to three properties: potential; connectedness and resilience. Whilst this representation may be appropriate for some ecological systems, its validity has been questioned by some researchers (i.e. Janssen *et al.* 2006, who found no simple connectivity to resilience relationship). Holling and Gunderson (2002) themselves stated that a system can become stuck within one region of the three dimensional space defined by the three properties. In the context of a farm as a 'system' it can be argued that the adaptive cycle metaphor is not appropriate as a farm differs in its behaviour from a socio-ecological system. Instead it is appropriate that a farm is seen as a component within an SES (allowing considerations of spatial and temporal scales beyond that immediately affecting farm management).

However, as Gunderson and Holling (2002) state "*No system can be understood or managed by focusing on it at a single scale. All systems (and SESs especially) exist and function at multiple scales of space, time and social organization, and the interactions across scales are fundamentally important in determining the dynamics of the system at any particular focal scale. This interacting set of hierarchically structured scales has been termed a 'panarchy*'". Similarly, Reidsma *et al.* (2010) state that, in order to accurately understand farm-scale impacts and adaptation, assessments should consider responses at different levels of organization. Studies of farm scale dynamics and how they may alter as a result of climate change can inform how larger scale process within an SES may be impacted and what potential changes an SES may experience.

2.4 Approaches for addressing multiple, complex and contested issues.

By their nature, holistic studies using Integrated Assessment approaches to research the impacts of climate change and to develop viable strategies for mitigation and adaptation[5] must encompass a wide field of interacting subjects and issues. This implies a high level of complexity in problem representation and tools for making estimates suitable to inform

[5] The IPCC give the following definitions. Mitigation: An anthropogenic intervention to reduce the sources or enhance the sinks of greenhouse gases. Adaptation: Adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities.

development of solutions. However, complex issues do not necessarily need complex approaches to study them, or to communicate methods and outputs to stakeholders (Nelson *et al.* 2007). Whilst detailed methods can be applied to investigate multiple interactions between variable state entities (i.e. farm management modelling), the acceptability of such study outputs for use by stakeholders may be compromised by the difficulty in establishing credibility due to both issue and representation complexity (McCown 2002). This is particularly true when considering multiple conflicting objectives from land use, including emerging ones such as greenhouse gas emissions reduction and carbon sequestration alongside existing food production and the provision of ecosystem services.

Integrated Assessment to research the impacts of climate change and to develop viable strategies for mitigation and adaptation encompass a wide field of subjects and issues. Often, detailed methods are applied to investigate multiple interactions between variable state entities influenced by multiple drivers of change. Acceptability of such study outputs for use by stakeholders may be compromised by the difficulty in establishing credibility due to both issue and representation complexity (McCown and Parton 2006). It is also important to recognise that individual farmers will respond differently to various influences and drivers, and that there is a wider range of variability between farms operating the same farm system (arable, livestock or mixed etc.) as well as diversity in the types of farming systems.

Challinor *et al.* (2009) argue that in order to generate knowledge for policy and adaptation, it is necessary to use a synergistic and holistic research framework that includes: the quantification of uncertainty; combining modelling approaches and observations focusing on fundamental processes; and careful calibration of models operating at appropriate levels of complexity to account for the main drivers (in these author's case, of crop production including biophysical and socio-economic factors). In considering the need for informative projections of potential future climatic conditions, Rivington *et al.* (2009b) advocate the use of a suite of approaches encompassing simple to complex methods that facilitate the envisioning of possible future conditions and hence the development of appropriate adaptation options with decision makers and other stakeholders. These authors present a range of approaches to investigate the impacts of climate change and potential adaptation options that exist at opposing ends of a detail and complexity spectrum: agro-meteorological metrics (simple); cropping systems modelling (intermediate complexity) to a whole farm model within an IMF (complex). Such a range is necessary to enable as comprehensive a picture as possible to be created of future conditions affecting farm scale dynamics, and to facilitate ease of communication of the modelling outputs. The simple to complex modelling approach also conforms with concepts of model validation, in that whilst it may be easier to evaluate simple models (having limited system representation) compared to complex ones (comprehensive system representation), there is an associated trade-off in that complex models (often made up of sub-model components) are harder to evaluate (i.e. Montieth 1996, and Fig. 1 in Bellocchi *et al.* 2009). Furthermore, the approach can deliver useful information, albeit limited in detail, generated from simple modelling approaches, whilst there is a greater risk that complex modelling may not be possible due to a wider range of constraints (input data availability, path dependencies due to data quality, calibration, sub-model coupling and software engineering).

However, there is need to establish credibility, salience and relevance (after Cash & Buizer 2005, cited in Matthews *et al.* 2008a) for the components making up the suite. In the case of this study, this can be addressed through the evaluation of climate model estimates, downscaling estimates to a site specific level, and by investigating the impacts of climate data uncertainty on model (i.e. CropSyst) estimates.

2.5 Climate model evaluation and downscaling (Chapter 3).

A key challenge in communicating the likely effects of climate change is in presenting the effects for spatial or organisational units that are within an individuals' experience, i.e.

farms, conurbations or water catchments (Droogers and Aerts 2005, Rivington *et al.* 2008b). A further challenge lies in helping them to understand the various sources of uncertainty in the climate scenarios so that they have appropriate levels of confidence in those projections (Maurer and Duffy 2005). The first challenge requires the development of downscaling methods to allow the outputs of Regional Climate Models (RCM) to be used in a site-specific context and that are appropriate to the processes of concern (Zhang 2005). The second requires the assessment, quantification and attribution of the various sources of uncertainty within the estimates. Without this analysis it is difficult to ascertain whether the additional error introduced by the change of scale is small enough not to invalidate the conclusions drawn from the study.

2.5.1 Climate model evaluation.

As a co-ordinated effort to evaluate and inter-compare climate models, the Coupled Model Intercomparison Project (CMIP) started in 1995, in which multiple AOGCM data was collated and compared (CMIP 2010). This approach enabled the identification of variation between models and formed the basis for reporting the uncertainty in climate projections in the IPCC Fourth Assessment Report (IPCC 2007a). Similarly, for the UKCIP02 climate projections, which utilised the HadCM3 and HadRM3, comparison was made between the Hadley Centre GCM and eight others (Hulme *et al.* 2002). This showed that the Hadley models' (HadCM3a, b and c) estimates of temperature and precipitation lay approximately in the mid range of the other GCM, but this may reflect the wide spatial and temporal variation between the eight models' projections.

Whilst it is useful to evaluate and inter-compare between GCM to illustrate the range in variation of projections (i.e. Ruosteenoja *et al.* 2003), in order to better understand the uncertainty, a further issue lies in the differences in spatial scale of representation of climate model estimates and impacts assessments. RCM produce estimates for grid cells that are typically for both historical (hindcast) and future time periods with a scale of spatial representation in the order of 50×50 km for the HadRM3 RCM used in this study (see Fig. 3), or 25×25 km scale used for the UKCP09 projections (Murphy et al. 2009) and, for example, the ENSEMBLES project covering Europe which used both spatial scales (van der Linden and Mitchell 2009). However, climate change impact, mitigation and adaptation studies increasingly consider spatial scales with a finer resolution than this. The availability of hindcast data from RCM permits observed and estimated data to be compared for the locations where the observations were made (Turnpenny *et al.* 2002). The quality of estimates and thus the utility of future scenario data for particular applications can thus be assessed (Moberg and Jones, 2004).

It is assumed that RCM hindcast data for a particular grid cell will be 'characteristic' of observed data from individual sites within the cell (i.e. having variables with similar temporal distribution patterns and value ranges), where the site has topographical and elevation traits similar to the mean of the cell. The differences between RCM estimates and observations from a particular site arise from two sources. First, differences in topography, elevation, distance to the sea, land cover (particularly for coastal sites and where a significant proportion of a RCM cell consists of water) and other geographical factors, between the site and the cell average. The second is related to the adequacy of the RCM in representing the climate processes that result in spatial variability. There are obviously micro-and meso-climatic effects that an RCM cannot be expected to represent, such as frost hollows or coastal fog. It is likely, however, that there will also be systematic differences due to the RCM structure and a parameterisation intended to achieve the best fit across the whole RCM area.

Since the RCM representation, structure and parameterisation are common to both the hindcast and future scenarios, then downscaling factors (DF) found by comparing observed with hindcast data may be used to downscale estimates of future climate for particular sites

(Rivington *et al.* 2008c). This will improve the reliability of site specific CC studies by reducing the likelihood that the estimated CC impacts are an artefact of the differences between site characteristics and their representation within the RCM.

Rivington *et al.* (2008b) compared precipitation, maximum and minimum air temperature, and solar radiation hindcast data produced by the Hadley Centre's HadRM3 RCM with observed data for 15 locations within the UK for the period 1960-1990 (see Chapter 3). Their aim was to develop a protocol for identifying systematic errors in RCM estimates for a range of locations and develop site-specific DF to reduce the differences between observed and modelled hindcast data. The overall purpose was that the resultant DF can then be used to adjust future estimates to correct for biases in the modelling of the climate processes *within* the RCM, i.e. *modelling uncertainty* (Murphy *et al.* 2004), and differences between the characteristics of the RCM grid and the specific location (i.e. *representation uncertainty*). This procedure does not deal with *scenario uncertainty* (Jenkins and Lowe 2003) in the estimates of future greenhouse gas (GHG) emissions and depends on the availability of appropriate hindcast data for any GHG scenario.

In terms of using future projections to aid development of adaptation and mitigation strategies, where uncertainties in RCM estimates and affect on CC studies remain unquantified, then evidence-based decisions become infeasible. Introduced systematic biases may lead to erroneous decisions being made and inappropriate actions being taken. Hindcast RCM data provide a unique opportunity to assess the nature of the uncertainty that would be introduced into systems models' predictions by the use of RCM rather than site specific information. Whilst the daily data from Global Circulation Models (GCM) and RCM can only be indicative of future conditions, with potentially large changes in data resulting from small changes in model structure or parameters, such data are those that will be used in impacts studies. By identifying any systematic biases and minimising them for particular locations through the use of downscaling methods, the robustness of any decisions based on RCM estimates for future climates will be significantly improved.

Much of the testing of RCM data has been conducted with the aim of improving the predictive performance of the models themselves e.g. Peng *et al.* 2002, and Antic *et al.* 2006, with rather less testing of the utility of estimates as part of particular impact assessments. Examples of exceptions include Bell *et al.* (2004), who performed a model versus observed validation exercise as part of a larger study of growing season length and extreme temperatures and precipitation in California.

Studies that have compared estimates with observed data tend to focus on individual weather variables at regional scales (i.e. Achberger *et al.* 2003), though some consider site-specific data, i.e. Fowler *et al.* (2005), who tested HadRM3H RCM for extreme rainfall events at 204 sites in the UK. Though the model provided good estimates of return periods for up to 50 years, it exaggerated the west to east rainfall gradient, leading to over-estimations in some higher elevation western areas, and under-estimation in the east. Jones *et al.* (2004) tested the Rossby Centre Atmospheric RCM, RCA2, and found that the model tended to over-estimate the number of small precipitation events, which impacted on surface temperatures and cloud-radiation interactions.

Moberg and Jones (2004) tested the HadRM3P model estimates of daily maximum and minimum near-surface temperatures for the period 1961-90 for 185 meteorological stations across Europe. Their analysis was primarily based on the model-minus-observed values for mean annual and seasonal temperature differences, though results for daily differences (forming the annual temperature cycle) were given for six locations. They found large spatial variations in the ability of the model to reproduce the historical weather well. It performed well in the UK and some other locations between 50 and 55ºN, with differences generally being ± 0.5 ºC, but other areas showed differences of up to ± 15 ºC. Whilst this study provided valuable information about the degree of spatial variability in the quality of estimates of temperature, it was insufficiently detailed to show the spatial pattern of daily differences. For a single site (Florence, Italy) Moriondo and Bindi (2006) concluded that the HadCM3 GCM and HadRM3P RCM were not able to recreate the maximum and minimum temperature patterns for most of the year, with both (particularly the GCM) failing to produce estimates close to the seasonal means. Differences have not only been found for temperature and precipitation. Kim and Lee (2003) found that surface insolation was generally over-estimated in an eight year hindcast simulation for the Western United States with the differences being smaller over land than over the sea.

2.5.2 Downscaling climate model estimates.

A range of techniques exist for downscaling (or translation across scales) data produced at the GCM scale in order to make projections that are more representative of finer spatial scales and therefore of higher utility to support regional and local scale research. The two most commonly used approaches are dynamic and statistical (alternatively called empirical) downscaling. In dynamic downscaling, regional climate models are nested within a GCM and driven by conditions from the GCM, regional specific data and equations (i.e. Murphy 2000, Druyan *et al.* 2002, Druyan *et al.* 2010). Whilst this approach have the capabilities to produce hindcast estimates that match well with observed data (i.e. Moberg and Jones 2004), and therefore projections that potentially represent well the local conditions, they are computationally demanding.

Statistical downscaling methods exist across a range of complexity (Georgi *et al.* 2001), from multiple regressions linking observations to functions with a GCM (Murphy 2000), to combinations of statistics and other methods such as artificial neural networks (Hewitson and Crane 1996, Wilby *et al.* 1998). It can be applied as an alternative, or supplement to dynamic downscaling, or as a combination of both (i.e. Oh *et al.* 2004). Statistical downscaling aims to identify empirical links between the large scale patterns and processes (or predictors) from GCMs with characteristics of a localised climate (i.e. through predictands such as properties of temperature, precipitation, cloud cover etc). As such the success of statistical approaches depends on the availability of suitably long time-series of observations. Some statistical approach focus on a single weather variable such as precipitation (i.e. Widmann *et al.* 2003, Hellstrom and Chen 2003), and for a specific purpose, such a river flow research (Maurer and Duffy 2005), but are generally multi-variable based. (i.e. Wilby *et al.* 2002). Advantages over the dynamic methods are that statistical approaches are not limited in scale, that is they can potentially produce projection data for spatial scales finer than those of RMCs, and the methods are less computationally demanding. A limitation of the statistic approach is that it relies on the assumption that the relationships between large scale predictors and fine scale predictands will persist under a changed climate. This also applies to other methods such as bias correction (Rivington et al. 2008c) (see Chapter 3).

Other approaches include the use of weather generators driven by GCM or RCM estimates to produce data at a finer spatial scale, and potentially for longer time series (i.e. Semenov and Barrow 1997, Kilsby *et al.* 2007). Such tools can be used to produce gridded data, as with the UKCP09 climate projections at a scale of 5× 5 km (UKCP 2010), though these have the disadvantage of not being spatially coherent (each 5× 5 km cell is independent from each other).

Beyond these approaches, there is little evidence in the literature of non-statistical based methods for regional to specific sites. Exceptions include the method developed by Ines and Hansen (2006) to interpolate the frequency and intensity distribution of daily precipitation from a GCM to a specific site in Kenya. Similarly Zhang (2005) downscaled monthly GCM precipitation and temperature data using transfer functions for one site in Oklahoma, USA. Kleinn *et al.* (2005) used correction factors to adjust RCM precipitation and temperature data used within a model chain for assessing stream flows within the catchment of the River Rhine. Similarly, Hay *et al.* (2002) in applying magnitude based bias corrections to the RegCM2 model, found that estimates improved the overall output from a basin scale hydrological modelling, but corrected data did not contain sufficient daily variability to match observed weather data. Baigorria *et al.* (2007) also found bias correction improved values of monthly statistics for a climate model ensemble compared against original hindcasts. Wood *et al.* (2004) conducted a detailed assessment of simple statistical downscaling methods (linear interpolation; spatial disaggregation; bias-correction and spatial disaggregation) applied to a Parallel Climate Model (PCM) and an RCM, but compared to a gridded climatology of precipitation and temperature. The bias-correction and spatial disaggregation approach gave the best results when the adjusted climate estimates were used within a hydrological model.

Whilst procedures that assess the quality of predictions and associated uncertainty at the regional scale for seasonal averages (i.e. Giorgi and Mearns 2003) provide valuable indications of overall model performance, they cannot be used to assess the accuracy of estimates at specific locations for periods of only a few days. Although researchers have compared RCM estimates with spatial aggregations of observed data (Frei *et al.* 2002), and for time scales longer than single days (Vidale *et al.*, 2003), neither comparison produced daily multi-variable data at a spatial scale suitable for site-specific studies.

This knowledge of model evaluation and downscaling has particular relevance in helping to better understand a more complete picture of uncertainty in projecting future climate change impacts. The next section follows on from this by looking at how input weather data quality affects the estimates made by models representing environmental processes.

2.6 Modelling uncertainty and data quality (Chapter 4).

2.6.1 Data used in impact studies.

Part of the rationale for Chapter 3 is to better understand how biases in RCM estimates effect CC impact studies. A primary approach in investigating and communicating the effects of CC is through the use of simulation models. A key area of uncertainty in modelling the potential impacts of CC on environmental entities and processes such as crops, ecosystems and hydrology, is the quality of data for future weather projections. It is therefore essential to understand how uncertainties introduced to such models will manifest themselves when using estimated input climate data (this is covered in Chapter 4). The uncertainty introduced into biophysical systems models due to the input weather data can be significant (Rivington *et al.* 2006b). For example, Nonhebel (1994a) showed that the use of mean monthly instead of daily data in a crop simulation model resulted in an over-estimation of potential production by 5-15%, and up to 50% in water-limited production in dry conditions. Nonhebel (1994b) also found that inaccuracies in solar radiation of 10% and of daily temperature of 1°C resulted in errors in grain yield estimates of up to 1 t ha^{-1}, and up to 10 days difference in the duration of the vegetative period (crop emergence to flowering) in cereals.

Maintaining meteorologically appropriate, synchronised relationships *between* individual weather variables is essential for models that represent entities with non-linear responses to driving variables such as biological systems (Nonhebel 1994a) and hydro-chemical processes (Soulsby 1995). Thermal time accumulation, which depends on the difference between daily maximum and minimum temperatures, is the key driver of plant and insect phenological development. Systematic errors in the estimation or synchronisation of either maximum or minimum temperature will result in predictions of either faster (earlier) or slower (later) development, with corresponding impacts on associated management (i.e. crop) or behavioural (i.e. plant-insect-predator) responses.

Projection data from climate models are often used within simulation modelling based CC impacts, mitigation and adaptation studies. However, as stated above, there are substantial differences in spatial scale at which CC projection data are produced and that at which impacts, mitigation and adaptation studies are conducted. These mis-matches between coarse resolution projections from climate models and the fine resolution data requirements of environmental models are a major obstacle for assessing site-specific CC impacts (Zhang

2005, Zhang 2007). Synchronisation of weather variables (precipitation, *Tmax*, *Tmin* etc.) becomes critical when considering extreme events (Benestad and Haugen 2007). It is therefore essential to understand how uncertainties in the input CC projection data manifest themselves within simulation models, and subsequently on how such information is used. It can be argue that without some understanding of this introduced uncertainty, the utility of such studies is greatly reduced by potentially producing misleading results.

Weather data from different sources that have similar statistical properties can produce different environmental model estimates, for example crop yields (Aggarwal 1995, Rivington *et al.* 2006b, Nui *et al.* 2009). The spatial scale of climate representation (GCM or RCM) will also determine the utility of environmental model outputs, with better estimates being associated with finer resolution climate models (Mearns *et al.* 1999). Similarly, downscaling methods can result in different outputs from models used in impact studies (Mearns *et al.* 1999, Zhang 2007). This is partially due to the non-linear responses of biophysical processes represented within environmental models (i.e. Nonhebel 1994a, 1994b).

2.6.2 Uncertainty in model estimates.

Few researchers quantify the impacts that data and parameter uncertainty have on the quality of model estimates. In applications of models to engineering problems, assessments are often made of the uncertainty that input data quality may introduce (J. P. Norton – personal comment). Where models are used for decision support and aiding strategic planning, there is a requirement that the quality of model estimates is assessed in advance, or that the decision support outcomes be made insensitive to the estimation uncertainty (Norton, 2003). However, it is rare that natural systems researchers publish the uncertainty in model estimates that may arise as a result of the quality of input data. Martorana and Bellocchi (1999) discuss uncertainty relevant to agro-ecosystem models, highlighting a classification of five uncontrolled variable sources of uncertainty: inputs; initial values; measurement errors in observations; structural and operational uncertainty. Bellocchi *et al.* (2009) further highlight the need for input data quality evaluation as part of an overall model uncertainty evaluation and validation process.

It is useful, in order to reduce it, to distinguish uncertainty arising from the lack of information (degree of confidence) and that due to temporal and spatial variability (Heuberger and Janssen 1994). Weather data can be seen to fall into both categories, as errors can occur when measurements are made and they have potentially large, and either continuous (i.e. temperature) or discontinuous (i.e. precipitation) spatial and temporal variability. Whilst a number of methods exist to investigate the relationships between model estimates and inputs, the more easily applied methods may still give inaccurate estimates of uncertainty. Methods that do, tend to be either difficult to apply or require considerable computational effort (Tyagia and Haan 2001). This implies that, in order for a basic level of uncertainty analysis to be applied more regularly to model applications, a simple but reliable method is required.

2.6.3 Meteorological data as a source of uncertainty.

Heinemann *et al.* (2002) showed that the accuracy of rainfall observations is critical for the simulation of crop yield and that the variability of simulated estimates is directly correlated to the accuracy of model inputs. This emphasizes the importance of data quality (accuracy of measurement), as well as site-specific representation. Xie *et al.* (2003) evaluated the importance of input variables on the yield estimates made for maize and sorghum by the ALMANAC model. They concluded that, in a dryland environment, rainfall and then solar radiation were the most important of the meteorological variables for non-irrigated crops, and solar radiation where irrigation was applied. These authors recommended the use of the closest weather station as an appropriate substitute source of meteorological data. However, Rivington *et al.* (2003, 2006b) found there could be substantial levels of uncertainty introduced by using neighbouring station data. Aggarwal (1995) tested the relationships between the uncertainty in crop, soil and meteorological inputs with the resulting uncertainties in estimates of yield, evapotranspiration and crop nitrogen uptake, within a deterministic crop growth model. It was then possible to identify the ‘uncertainty importance’ of an input for a given scenario, concluding that in rain fed environments soil and weather inputs were dominant over crop parameters in introducing uncertainty.

Solar radiation is a key variable as it is used, amongst other things, as part of the estimation of evapotranspiration (ET) and biomass accumulation. Bellocchi *et al.* (2003) tested the impacts of three air temperature based methods for estimating solar radiation data on the estimates made by CropSyst on reference crop ET and subsequent determination of above ground biomass (AGB), at twenty locations worldwide. The solar radiation models tested where able to provide both good and poor estimates, with subsequent propagation of errors in ET and AGB. The results showed that each source had different levels of performance, in terms of yield estimates, with each geographical location and seasonal patterns.

Hudson and Birnie (2000) showed that the time period from which meteorological data were taken had an impact on the results of a land capability classification model. This implies that model output determined from meteorological data from one time period vary from those derived from another. Nonhebel (1994a), showed that average weather data produced different simulation results than daily data (an over-estimation in potential production of 5-15% and up to 50% in water limited production in dry conditions), due to i). the response of non-linear relationships within the model used, where average input did not give average output, and ii). the large variability in daily weather data being different from the average value.

What the above means in terms of making projections of CC impacts within this study is clarifying that there is a sequence of modelling processes (climate modelling and use of estimated future weather data used within environmental models) where error propagation can occur. By understanding the sources of uncertainty and how they manifest themselves as estimation errors throughout the sequence, it becomes possible to better interpret the overall results and place a value judgement on their utility. It can be argued that the findings from an Integrated Assessment not using an evaluation and error quantification approach may be misleading.

2.7 Agro-meteorological metrics as indicators of change (Chapter 5).

Farmers, foresters and other land managers may pose questions on potential climate change impacts and adaptations that simple summaries (i.e. annual or mean monthly values) are unable to answer. There is therefore a need to develop methods for communicating the likely impacts in a familiar form and that contain sufficient detail to make informed decisions. Observed weather data can be used to derive secondary estimates (e.g. evapotranspiration) or indicators (e.g. field access periods, last day of spring frost etc.) in order to support land management decision making. Such values, collectively referred to here as agro-meteorological metrics (Ag-Metrics), when derived from future climate projection data from climate models provide important indications of future bio-climatic conditions within which agriculture, forestry and other land uses will have to operate (Bellocchi *et al.* 2004, Feng and Hu 2004, Rivington *et al.* 2008a). Information on potential agro-meteorological conditions will be highly valuable when assessing the risks of CC impacts and in developing appropriate mitigation and adaptation strategies, policies for land use and investigating potential market responses (Matthews *et al.* 2008a).

Ag-Metrics can provide information that is useful in respect of mitigation targets and to commercial interests in terms of indications of shifts in production capabilities and limitations. These can then be put into context with economic and policy projections and the multi-functional requirements of land use. As such they can provide a useful supplement to other forms of information, such as from model based studies, and to aid decision making via decision support systems (i.e. DESSAC, Brooks 1998), both at the farm and policy related scales, and for tactical and strategic purposes. However, the level of detail and inter-relationships between processes (or variables) tends to be lower (more simple) in the Ag-Metrics compared with conventional model outputs.

In terms of tactical decision making, Ag-Metrics can be run in real time and disseminated via the internet (Stefanski and Sivakumar 2006). Whilst crop models can be used to investigate the interactions of plants, soils, pests and management, agro-meteorological information is needed to translate such research into practical advice on aspects such as managing water or pests, particularly in integrated pest management practises (biological control, resistant crops and habitat manipulation) (Strand 2000). Hence Ag-Metrics can be seen as an intermediate level of detail above that provided by climate summaries, but lower in detail than crop models. For long term overall strategic planning, it is important to know what the fundamental shifts in conditions (i.e. soil water balance, rainfall distribution, temperature etc.) that determine land use options and their associated management practises are likely to be. They help to identify the possibility of thresholds being crossed, and when land uses are no longer viable in their existing state. Such fundamental indications are vital if inappropriate adaptation strategies are to be avoided. Using a Land Capability for Agriculture classification method (MLURI 1991) reproduced under a future climate scenario in Scotland, Brown *et al.* (2008) showed a reduction in climatic constraints on land capability for agriculture in some locations (those that are currently cool and wet) but an increase in others (those that are considered ‘prime agricultural land’ due to a potential increase in soil moisture deficit). This raises the potential for an increase in productive land area, but points towards greater yield variability with growing conditions being limited by soil moisture, and potential risks of increased carbon loss from organic soils. The Ag-Metrics provide more detailed site specific information about the changes in climatic and climate–

soil related constraints, and can be used to make specific choices by decision makers about the system they work with. As such they are powerful tools for knowledge transfer and aiding social learning (McCrum *et al.* 2009), as they present information characterising properties that stakeholders (farmers, governments etc..) are familiar with under present climate conditions and illustrate how they will change in the future (Matthews *et al.* 2008a).

2.8 Crop Production (Chapter 6).

In trying to understand the impacts of climate change on crop production, many previous research efforts have considered the responses of crops to elevated CO_2 (biomass accumulation and physiological processes, i.e. Manderschied and Weigel 2007) including a doubling of current CO_2 concentrations, i.e. Free Air Carbon dioxide Enrichment, (FACE), experiments. Others have combined CO_2 elevation and projected future climatic conditions (i.e. Reilly *et al.* 2003). Plants respond to increases in atmospheric CO_2 by increasing photosynthesis and reduced transpiration (due to reduced stomatal conductance) and improving nitrogen use efficiency (Leakey *et al.* 2009), giving a potential gain in biomass production (Qaderi and Reid 2009), though there is debate as to the overall trade-offs in physiological responses and effect on food production (Tubiello *et al.* 2007). For example, higher temperatures result in a shortening of winter wheat grain filling duration and reduced yields, but under elevated CO_2 (684ppm) grain weight increases even at higher temperatures (Wheeler *et al.* 1996a), with a slightly higher Harvest Index under higher temperatures and CO_2 than under just higher temperature. Some results suggest that the benefits to winter wheat grain yield from CO_2 doubling are offset by an increase in mean seasonal temperature of only 1·0 °C to 1·8 °C in the UK (Wheeler *et al.* 1996b). Higher CO_2 concentrations (i.e. 700 ppm) also result in increased leaf area in winter wheat due to increased tillering (Wheeler *et al.* 1996b), a response that is not included in CropSyst. Similarly, there is a range of responses (from C_3 plants) to seed production in relation to plant and seed nitrogen concentrations under elevated CO_2 (Hikosaka *et al.* 2011). There is also evidence that higher levels of ground level ozone (O_3) may counter the potential elevated CO_2 benefits by reducing stomatal closure control by plants, and affecting yields across a range of crop types (Feng and Kobayashi 2009). In the case of wheat, future O_3 concentrations of 51-75 ppb could result in a yield reduction of as much as 10 % beyond that under current O_3 concentrations (c. 26 ppb). These are response functions not represented by crop models like CropSyst.

A question that therefore arises is whether the current state of crop model develop is sufficient to enable meaningful estimates of the complex mix of responses to elevated CO_2, temperature, water availability and other factors such as effects of plant nitrogen. There are likely to be differences in responses between crop types and photosynthetic pathways (C_3 or C_4) and between perennial and annual plants (Kimball *et al.* 2002), which coupled with regional variations in climate change magnitude add to the spatial and temporal mix of overall global scale crop production responses. Also, it is likely (IPCC 2007b) that even if GHG emissions ceased now, there will still be some warming and associated changes to the climate, with corresponding adaptations to crop management that may not incorporate utilisation of elevated CO_2 benefits.

However, the current aim is to limit global temperature rise to 2°C above pre-industrial levels (UNFCCC 2009), potentially by achieving a maximum atmospheric CO_2 stabilisation concentration of c. 450 parts per million (ppm) (IPCC 2007c) by 2050. The current concentration is 387 pmm (NOAA 2010). This implies that crop responses to an additional 60 to 70 CO_2 ppm are unlikely to result in significant increases in yields. Hence modelling experiments of crop production using high CO_2 concentrations may have limited relevance. However, localised CO_2 concentrations in urban and city areas can be considerably higher (Kim *et al.* 2008), but are far less significant in food production terms.

These factors overall indicate that there is value in initially estimating the response of crops to altered weather conditions under climate change, but without including elevated CO_2 effects. Possibly of greater significance, and certainly easier to model, is that growing conditions as determined by the weather and soil interactions are changing and will continue to change under a future climate (Fuhrer 2003). Extreme weather events are likely to adversely affect production systems through increased water stress, droughts, flooding etc., whilst also modifying the risks of pests and pathogen outbreaks (Easterling *et al.* 2007). Potentially of greater importance than elevated CO_2 in cereal production is the change in temperature variability, particularly the frequency and timing of hot events (Wheeler *et al.* 2000) and related to water availability. For example, extreme heat stress at anthesis can reduce wheat grain yield by 40% (Wollenweber *et al.* 2003), and CO_2 concentrations above 450ppm may cause deleterious effects on grain yield quality in rice, maize and wheat (Erda 2005). Increased soil water deficits over longer periods than present may impose crop choice restrictions (Brown *et al.* 2008, Rivington *et al.* 2009b). What is seen to be desirable is to better model the combined effects of extreme heat, water limitations and elevated CO_2 concentrations on crop growth and development (Rivington and Koo 2011).

There is debate on the role of elevated CO_2 on crop production. For example, Long *et al.* 2006 claimed that earlier models based on non- FACE experiments had over-estimated yield increase due to elevated CO_2 compensating against potential reductions due to higher temperatures and decreased soil moisture. However, Tubiello *et al.* (2007) disputed the findings of Long *et al.* (2006) on the basis of technical inconsistencies of FACE and lack of statistical significance. Across the literature there is evidence of benefits of elevated CO_2, such as increasing photosynthetic carbon gain and net primary production, improving nitrogen and water use efficiency (Leakey *et al.* 2009) but with potential decreases in plant nitrogen concentrations, affecting feed quality (Weigel and Manderscheid 2005). There is also a large range in the level of detail to which crop models have been calibrated against elevated CO_2 experiments. In a recent survey of crop modelling, 36.5% of respondents said the model they worked with had not been calibrated against elevated CO_2 experiments, but only 33.6% said the models had been (Rivington and Koo 2011).

Given the relative complexity of trade-offs between the benefits and disadvantages of elevated CO_2 on crop production, and the targets for climate stabilisation, it is logical that studies using crop models with limited, or unquantified uncertainty in CO_2 response representation (i.e. CropSyst) are best used initially without elevated CO_2. Again this indicates a need to focus on issues of crop responses driven by the weather within a future climate (i.e. Porter and Semenov 2005), rather than the physiological response to elevated CO_2. Also, the decisions in management adaptations by farmers are more likely to be in response to the weather conditions, rather than elevated CO_2. In the context of these issues and this thesis, it is worth recognising the limitations of using a single crop model given the variety of estimates possible from a range of models (see Challinor *et al.* 2009) and weather data sources (Rivington *et al.* 2006b).

In considering individual farm management decisions it is also necessary to consider the response of crops at a global scale, in that production may increase in some regions and decrease in others (i.e. Tan and Shibasaki 2003), and as stated above, variations in crop type (photosynthetic pathways, legumes and non-legumes etc.) with consequences on supply and demand. The timing of climate change impacts also occurs with a probable increase in oil and gas prices (i.e. IEA 2009) and associated impacts on energy used, coupled with projected population increases (one estimate peaking at 9 billion by 2075, UNDESA 2004). Dietary changes towards higher protein from meat consumption are also likely, i.e. Delgado (2003) estimated that by 2020 the share of developing countries in total world meat consumption will increase from the current 52% to 63%, with developing countries consuming 107 million metric tons (mmt) more meat and 177 mmt more milk than they did in 1996/1998, compared to an anticipated developed-country increase of 19 mmt for meat and 32 mmt for milk, This potential change in regional production capabilities and demand will have consequences for food security and distribution availability (Parry *et al.* 2001, IPCC 2007a) and commodity prices (Nelleman *et al.* 2009). This implies that the farm-scale decision criteria determining land use and management (crop choice, rotations, enterprise mixes) in the near future may be substantially different from those at present. Thus adaptation within crop based land uses (and others) will be a complex mixture of on-farm biophysical (soils, micro-climate), social (labour and skill) and economic (financial and structural capital) constraints, and external policy and economic drivers that are largely unpredictable. A key task for crop production modelling for a future climate is therefore to provide an indication of the sign of change of key factors such as yield, input requirements (i.e. fertiliser, machinery and labour) in order to better quantify impacts on the social and economic interactions.

Based on the above range of responses to a combination of elevated CO_2, higher temperatures and varied water and nitrogen availability, coupled with greater awareness among farmers of improved management adaptations to take advantage of the potential benefits, it appears to be a reasonable assumption that crop yields can increase in the future, albeit by a smaller amount than originally estimated (Leakey *et al.* 2009). Reported values for winter barley (based on FACE testing), are 14.4 % increase in biomass (Weigel *et al.* 2006), and 20 % for spring barley (Saebo and Mortensen 1996), whilst Ewert *et al.* (2005) estimated a 16 % increase in wheat by 2050 under the SRES A1 scenario.

However, modelling the combined physiological effects of elevated CO_2, temperature, water and nitrogen responses by plants though remains a substantial challenge. Hence estimating crop response to just altered weather conditions serves as a starting point upon which more detailed estimates based on responses to CO_2 can be based. Yield estimates derived from an altered climate only can potentially be re-interpreted assuming that actual future yields under elevated CO_2 could be higher, by as much as 14-20 % (as per Saebo and Mortensen 1996, Weigel *et al.* 2006, Ewert *et al.* 2005 and other references cited above) or scaled back relative to a target stabilisation CO_2 concentration.

2.9 Grass modelling (Chapter 7).

The representation of grass production systems within a modelling environment is problematical due to the complex nature of grass growth and response to grazing or cutting, particularly in mixed species swards (Thornley 1998). The plasticity of grass morphology and physiological responses to disturbance and age of sward and species composition combined with multiple management influences (and that grass sward may contain leguminous species like clover), and differing aims of the modelling exercise (physiological responses, decision support etc.), has resulted in many strategies for grass simulation within models (i.e. Johnson and Thornley 1983, Thornley 1998, Hutchings and Gordon 2001, Barrett *et al.* 2005) and at differing spatial scales (i.e. Gimona *et al.* 2006). The sum total is a range of models that utilise either empirical, process or mechanistic approaches at differing levels of complexity, where complex models are not necessarily better at reproducing observed production (Skinner *et al.* 2009) and separate models may have different strengths and weaknesses in simulating individual system components (nutrient cycling, response to climate, plant growth), making it difficult to select a single best model (Bryant and Snow 2008).

Part of the development of this thesis has involved collaboration with the CropSyst development team at Washington State University. CropSyst is a generic cropping systems model originally designed for cereal based systems in the North-western USA. The inclusion of grass as a perennial crop required the addition of new features within the model. Of particularly importance have been components and parameters for handling senesced leaf material and incorporation into soil residue (organic matter pools) and to control off-take by either grazing or mechanical cutting. However, parameters controlling physiological responses functions are limited in their ability to alter the growth form of the plant resulting from grazing or cutting. The underlying model structure of crop growth remained unchanged, hence there was a limitation placed on application of new parameters. Conversely, the full range of estimates made by CropSyst beyond crop growth, such soil water, nitrogen and organic matter dynamics, were available. The addition of the grass components are as yet unpublished and untested.

In respect of climate change effects on grass systems, responses vary between studies. Smit *et al.* (2008) provides estimates of increased production ‘in recent decades’ of permanent (0.25%) and temporary (0.5%) grassland in Europe, with production being highly correlated with annual precipitation and less than with annual temperature and length of the growing season. For future conditions, Parsons *et al.* (2001) concluded that there could be a small increase in grass production in the UK, with an associated increase in livestock production. However, the grass model used (SWARD, Armstrong *et al.* 1995) had a simple water balance component and growth based on a single balance equation of growth and removal by senescence and harvesting and that nitrogen was non-limiting. Also using the SWARD model, Armstrong (1996) found the dominant effect of a future climate scenario was to bring the onset of grass growth forward, with a subsequent drop in production rate during the summer due to water stress in response to a greater soil moisture deficit. Thornley and Cannell (1997) using the Hurley Pasture Model estimated an increase in productivity based on higher photosynthesis rates, but based on CO_2 concentrations up to 700 ppm and temperature increases up to 5°C. Topp and Doyle (1996) also found an extension to the length of the growing season, but that there was no significant increase in a pure grass two-cut silage system yield (based on a 2°C temperature increase) with CO_2 at 350 ppm. Under an elevated CO_2 concentration of 520 ppm, there was a significant increase in grass yield per silage cut. However, the grass modelling components of the above studies were not directly calibrated against observations of grass responses to elevated CO_2 and as per section 2.8, there are uncertainties associated with the ability of models like CropSyst to represent the combination of weather and soil variables with elevated CO_2. Hermans *et al.* (2010) also point out the importance of technological developments in increasing productivity in the past and how it will improve production in the future. These authors estimated a factor of 1.12 for grassland productivity increase due to technological advances by 2050 (under the SRES A1 scenario).

2.10 Integrated Modelling Frameworks.

The key challenge in developing an integrated assessment approach is in having a framework with a structure that in an equable way integrates different sources of information relevant to the whole system being studied (Rivington *et al.* 2004, Rivington *et al.* 2007, Ewert *et al.* 2009). Such a structure is best designed to be modular (as with crop models, i.e. Keating *et al.*, 2003), with each module being independent and capable of producing outputs of value separate from the overall framework, but with loose-coupling between modules in order to exchange data. Where the modules consist of models, this aids calibration and validation (Bellocchi *et al.* 2009). For whole-farm modelling, the key components are those that simulate biophysical processes, reflect management options available, and has appropriate external driver inputs to put internal constraints into context. Further value is added to the framework where it has a spatial context (Matthews *et al.* 1999). Such an IMF should be generic and flexible and capable of use for multiple purposes, i.e. climate change impacts (Rivington *et al.* 2007), or policy reform (Matthews *et al.* 2006a).

Rivington *et al.* (2007) further argued that an integrated assessment approach, combining simulation modelling with deliberative processes involving decision makers and other stakeholders, has the potential to generate credible and relevant assessments of climate change impacts on farming systems. The justification for such an approach is that while simulation modelling provides an effective way of exploring the range of possible impacts of climate change and a means of testing the consequences of possible management or policy interventions, the interpretation of the outputs is highly dependent on the point of view of the stakeholder. Inevitably, whatever the responses to climate change, there will be tradeoffs between the benefits and costs to a range of stakeholders. The use of a deliberative process that includes stakeholders, both in defining the topics addressed and in debating the interpretations of the outcomes, addresses many of the limitations that have been previously identified in the use of computer-based tools for agricultural decision support (Matthews *et al.* 2008b).

There is a risk within an integrated assessment framework, even allowing for a modular structure, that there are critical path or data dependencies. The essence of an IMF is its ability to integrate across a range of data or information sources, but if one or several such sources is unavailable or of insufficient quality, then the objectives of the whole IMF may not be met. However, valuable insights may still be gained from the individual components. Here the 'spectrum of model complexity' set out by Rivington *et al.* (2009b), where the IMF consists of simple to complex models, provides a sub-structure that allows meaningful results even when there is a breakdown in the critical dependencies. It does not however mean that outputs from the complex end can always be produced or have improved reliability.

2.11 Chapter Summary.

What this Chapter has demonstrated is that there is a considerable range in the approaches that can be made to investigate the impacts of climate change on farm scale dynamics, and that there is a considerable number of drivers of change beyond just the climate. Such complexity requires a suite of research approaches. These include a conceptual framework within which issues can be organised and assessed (resilience and adaptive capacity), modelling frameworks that enable multiple scales of representation and degree of complexity representation, and the need to evaluate issues of uncertainty and develop methods to either reduce it or make transparent the impacts that the uncertainty has on research studies. Fundamentally this Chapter demonstrates that, whilst external drivers such as policies and economics potentially have a greater influence on farm-scale decision making, the consequences of the biophysical impacts of climate change serves as a valuable starting point in developing adaptation options.

Chapter 3: Climate model evaluation and downscaling.

3.1 Abstract.

This Chapter evaluates the quality and utility of data produced by the HadRM3 RCM for use at the site-specific scale. Comparisons were made between observed weather data and modelled hindcast estimates at 15 sites in the UK. It was found that the RCM was able to reproduce observed data well for some variables and at some sites, but also the data consisted of substantial errors for other variables and site combinations. A conclusion was drawn that the type and magnitude of errors present in the hindcast data indicated that the future projection data would also contain such errors as to invalidate their use within site-specific CC impact, adaptation and mitigation studies. The HadRM3 estimates however were sufficiently close to the observed data as to imply that downscaling by bias correction could produce data that have reduced uncertainty and hence greater utility. A simple bias correction downscaling method is described and the estimates re-evaluated against observed data.

3.2 Introduction.

The work detailed in this Chapter is an compilation of two papers, Rivington *et al.* (2008b) on the evaluation of the HadRM3 RCM, and the subsequent development of a bias correction downscaling method and re-evaluation (Rivington *et al.* 2008c). In this Chapter a UK wide approach was taken by using observed data from 15 meteorological stations so as to better capture the spatial variation in RCM performance and ability of the downscaling method to improve data quality.

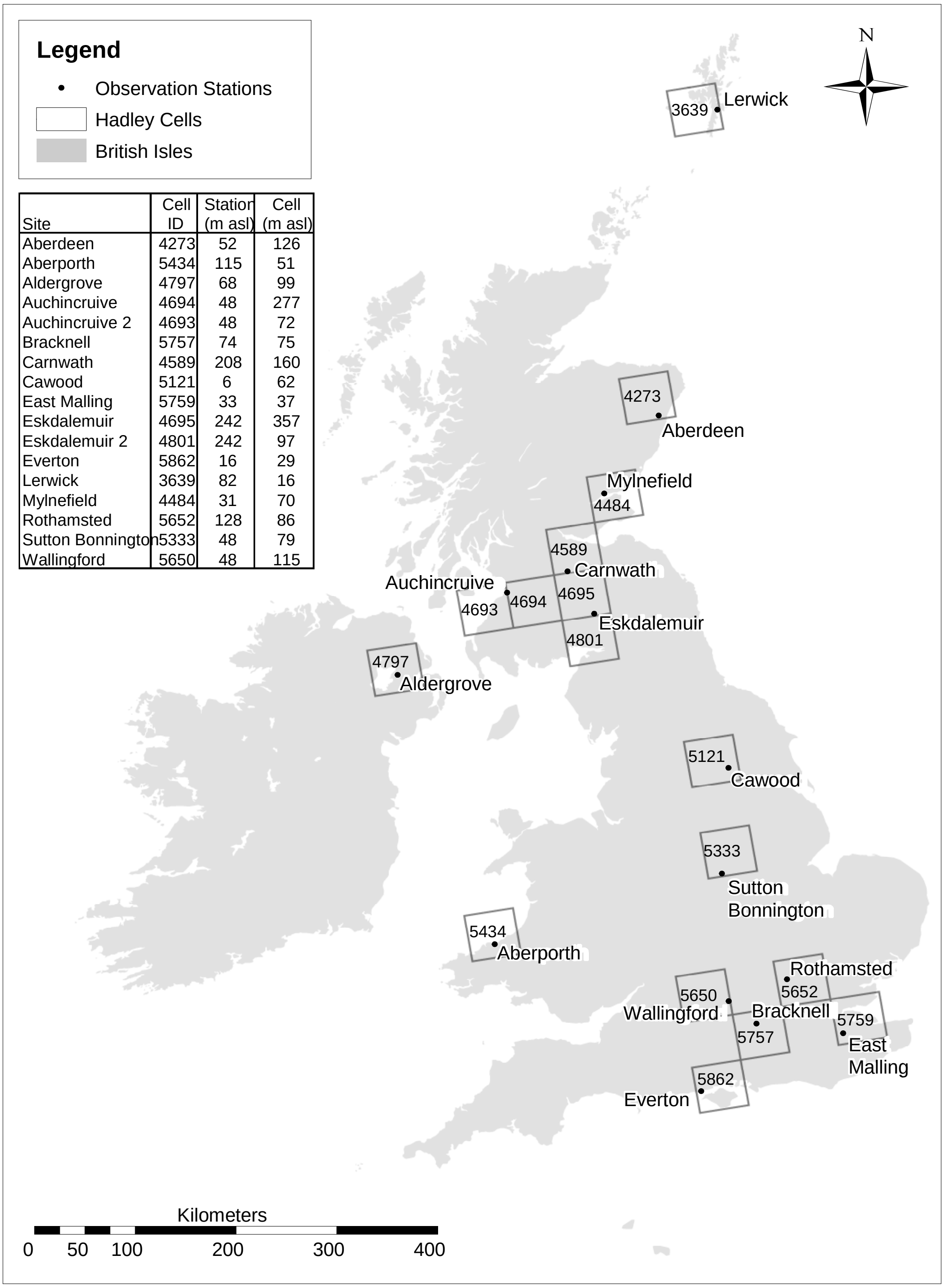
It is assumed that RCM hindcast data for a particular grid cell will be 'characteristic' of observed data from individual sites within the cell (i.e. having variables with similar temporal distribution patterns and value ranges), where the site has topographical and elevation traits similar to the mean of the cell. The differences between RCM estimates and observations from a particular site arise from two sources. First, differences in topography, elevation, distance to the sea, land cover (particularly for coastal sites and where a significant proportion of a RCM cell consists of water) and other geographical factors, between the site and the cell average. The second is related to the adequacy of the RCM in representing the climate processes that result in spatial variability. There are obviously micro-and meso-climatic effects that an RCM cannot be expected to represent, such as frost hollows or coastal fog. It is likely, however, that there will also be systematic differences due to the RCM structure and a parameterisation intended to achieve the best fit across the whole RCM area. Since the RCM representation, structure and parameterisation are common to both the hindcast and future scenarios, then downscaling factors (DF) found by comparing observed with hindcast data may be used to downscale estimates of future climate for particular sites. This will improve the reliability of site specific CC studies by reducing the likelihood that the estimated CC impacts are an artefact of the differences between site characteristics and their representation within the RCM.

Chapter 3 compares mean daily precipitation, maximum and minimum air temperature, and solar radiation hindcast data produced by the Hadley Centre's HadRM3 RCM with observed data for 15 locations within the UK for the period 1960-1990. The aim was to develop a protocol for identifying systematic errors in RCM estimates for a range of locations and develop site-specific DF to reduce the differences between observed and modelled hindcast data. The overall purpose was that the resultant DF can then be used to adjust future estimates to correct for biases in the modelling of the climate processes within the RCM, i.e. *modelling uncertainty* (Murphy *et al.* 2004), and differences between the characteristics of the RCM grid and the specific location (i.e. *representation uncertainty*). This procedure does not deal with *scenario uncertainty* (Jenkins and Lowe 2003) in the estimates of future greenhouse gas (GHG) emissions and depends on the availability of appropriate hindcast data for any GHG scenario.

In terms of using future projections to aid development of adaptation and mitigation strategies, where uncertainties in RCM estimates and affect on CC studies remain unquantified, then evidence-based decisions become infeasible. Introduced systematic biases may lead to erroneous decisions being made and inappropriate actions being taken. Hindcast RCM data provide a unique opportunity to assess the nature of the uncertainty that would be introduced into systems models' predictions by the use of RCM rather than site specific information. Whilst the daily data from GCM and RCM can only be indicative of future conditions, with potentially large changes in data resulting from small changes in model structure or parameters, such data are those that will be used in impacts studies. By identifying any systematic biases and minimising them for particular locations through the use of downscaling methods, the robustness of any decisions based on RCM estimates for future climates will be significantly improved.

The objectives for this Chapter are:

- Evaluate the quality of data estimated by the HadRM3 RCM for the hindcast period (1960 to 1990).
- Develop a method to bias correct differences between observed and modelled hindcast data in order to enable downscaling from region to site-specific scales.
- Use the bias correction method with projections of the future climate and generate climate projections representative of particular locations.
- Utilise the process of evaluation and downscaling to develop a better understanding of the uncertainty within climate modelling, errors within estimated data and how such errors may impact on uses of the data.



Site	Cell ID	Station (m asl)	Cell (m asl)
Aberdeen	4273	52	126
Aberporth	5434	115	51
Aldergrove	4797	68	99
Auchincruive	4694	48	277
Auchincruive 2	4693	48	72
Bracknell	5757	74	75
Carnwath	4589	208	160
Cawood	5121	6	62
East Malling	5759	33	37
Eskdalemuir	4695	242	357
Eskdalemuir 2	4801	242	97
Everton	5862	16	29
Lerwick	3639	82	16
Mylnefield	4484	31	70
Rothamsted	5652	128	86
Sutton Bonnington	5333	48	79
Wallingford	5650	48	115

Figure 3: Meteorological stations providing observed data and the position of their associated HadRM3 50×50 km grid cell, with the station and mean cell elevations (m a.s.l.) (Created by D.G. Miller).

3.3 Materials and methods.

This Chapter uses the observed and modelled weather data detailed in Chapter 1. A meteorological station was matched with its corresponding cell. Selection criteria for sites with observed data were the completeness of their data record, and their location in relation to an idealised uniform spatial distribution across the UK. The number of sites available for assessment was limited by the availability of S_o data. In two cases stations were within 2 km of the cell boundary (Auchincruive and Eskdalemuir), in which case the opportunity was taken to use the closest neighbouring RCM cells for comparison as well.

Based on the findings of Moberg and Jones (2004), no *a priori* adjustments to the modelled data were made to take account of differences in elevation or other climatologically significant topographic differences between the meteorological station and the mean for the grid cell. The mean elevation for each grid cell and meteorological station is given in Fig. 3.

This study consisted of four stages: assessing the quality of the hindcast estimates against observed data; development of downscaling factors (DF); re-assessment of downscaled hindcasts against observed; and application of DF to future projections.

3.3.1 Data quality assessment.

The first stage of the work compared modelled and observed data for the period 1960-90 for each weather variable at the 15 locations (17 cells).

3.3.1.1 Precipitation

Histograms were plotted to illustrate the frequency distribution of the magnitude of precipitation events (> 0 mm). For each precipitation event the Probability of Excedence (*Pe*) was calculated following Weibull (1961):

$$Pe\ (\%) = m/(n+1) \times 100. \qquad (1)$$

Where m is the rank order of each precipitation event, with $m = 1$ as the largest event and $m = n$ for the lowest, with n being the number of observations (in this case $n = 360$ days × 30 years). Where precipitation amounts are equal, they have the same m value. This method enables differences in the probability of occurrence of precipitation events of the same magnitude to be identified and avoids the problem of asynchronicity in the timing of precipitation. As such the method does not take into account the day of year that each data value represents (i.e. observed and modelled data of the same *Pe* may have occurred on different days). Using the ranked decreasing order of precipitation event, the difference (modelled – observed) and proportional difference, compared with the observed event magnitude ((modelled – observed) / observed) was calculated. The mean annual precipitation, magnitude of largest event and the mean number of days with no precipitation (dry days) were calculated. To assess the temporal distribution of events, plots of the 7-day (weekly) means were made.

3.3.1.2 Temperature

The mean daily values for *Tmax* and *Tmin* were calculated and plotted for the observed and estimated data. This enabled the magnitude of differences and their temporal distribution within a year to be visually assessed. The Root Mean Square Error (RMSE) and 2 tailed paired Student's t-test of the probability of equal means (P(t)) were estimated for comparison of observed and hindcast mean daily and highest and lowest values of *Tmax* and *Tmin* for a set of example locations. Mean daily *Tmax* - *Tmin* was calculated and plotted, in order to assess the model's ability to represent the daily temperature range. The highest and lowest daily values of *Tmax* and *Tmin* were plotted to examine how well the model was able to represent daily variability and extreme ranges. The mean annual *Tmax* and *Tmin* and highest and lowest temperatures were calculated, along with the mean number of days when temperature exceeded three thresholds: *Tmax* > 15 ºC, *Tmin* < 0 ºC and *Tmin* < -5 ºC. Plots were also made of the mean daily thermal time accumulation over the period of a year.

3.3.1.3 Solar radiation

Observed S_o data records are often incomplete for the 1960-90 period, hence analysis was limited to graphical representations using the difference between mean daily observed and estimated solar radiation. This difference in daily means helps to illustrate the temporal distribution of mean daily errors (over- and under-estimations) over the period of a year, indicating systematic model behaviour. This approach was taken to allow direct comparison of results with a previous study of the performance of three solar radiation models carried out by Rivington *et al*. (2005). Observed and modelled S_o data were also smoothed by calculating a 7-day running mean (mean of day 1 to 7, mean of day 2 to 8 etc..) and then plotted to emphasise the annual distribution pattern.

3.3.2 Development of Downscaling Factors.

Downscaling factors (DF) were developed to minimise the difference in means between the observed and RCM hindcast values for each weather variable. The DF were applied to the daily data. For *Tmax*, *Tmin* and S_o, three temporal intervals were tested for the application of the DF: annual (one DF for the entire year); growing season and non-growing season (2 DF, one for each season); and monthly (1 DF for each month). Further tests applied the DF by multiplication and addition. Initial investigation showed that the annual time period and the multiplication application methods were unsatisfactory. The seasonal time period (2 DF) improved the match between modelled and observed data, but contained unrealistic ‘steps’ at the day of change between seasons. The following details the best method, the application of monthly values of DF by addition (where DF can be positive or negative) to *Tmax*, *Tmin* and S_o.

3.3.2.1 Precipitation.

Precipitation DF were handled differently from the other weather variables in that a two stage approach was used. Firstly, a single value (DF_d) was subtracted from the value of every event to correct the number of days with no precipitation (0 mm) and reduce the difference in distribution of low precipitation events seen in Fig. 4. The value of DF_d was found by the implementation of an iterative loop, whereby an optimal value was found to subtract from each event value such that it minimises the mean number of observed – estimated dry days difference. If the event value – DF_d became < 0, then the value was set to 0. Hence DF_d is effectively a single optimal value of a precipitation event amount below which all data values $> 0 \leq DF_d$ can be removed. A significant number of very small (generally < 0.3 mm) modelled precipitation events are removed that then requires a second DF (DF_{mat}) to be applied to correct for both the model's original error in estimating mean annual total and the new reduced value. Here DF_{mat} is applied as a percentage increase to non-zero values, where the increase is proportional to the size of the modelled value, i.e. value + (value × DF_{mat}). The objective for DF_{mat} was to minimise the difference (D_{mat}) between the mean of the observed annual totals (O_{mat}) and the estimated mean annual totals (E_{mat}), where (D_{mat}) was found by:

$$D_{mat} = \overline{\sum_{i=1}^{n} O_{mat}} - \overline{\sum_{i=1}^{n} E_{mat}} \tag{2}$$

Precipitation DF do not take into account seasonality, as the distribution of the excessive number of small events was even throughout the year, and the DF_{mat} are applied proportionally to the magnitude of each event.

3.3.2.2 Air temperature and solar radiation.

Downscaling factors (DF_{Tmax}, DF_{Tmin} and DF_{sr}) were developed for *Tmax*, *Tmin* and S_o, respectively, where the minimised value was the difference between the observed and modelled sum of daily means per month,:

$$DF_{T\max} = \overline{O_{T\max\, ji}} - \overline{E_{T\max\, ji}} \tag{3}$$

and

$$DF_{T\min} = \overline{O_{T\min\, ji}} - \overline{E_{T\min\, ji}} \tag{4}$$

and

$$DF_{sr} = \overline{O_{sr\, ji}} - \overline{E_{sr\, ji}} \tag{5}$$

where $O_{Tmax\, ji}$ is the observed *Tmax* in the year *j* and day *i* per month (30 days) and $E_{Tmax\, ji}$ is the modelled *Tmax* in the year *j* and day *i* per month (and the same, correspondingly, for *Tmin* and S_o). Hence 12 individual DF were developed for each weather variable for each month for all years (i.e. one DF_{Tmax} applied to hindcast January 1960-90 data, one for February etc..).

3.3.3 Application of Downscaling Factors to future estimates.

On the assumption that uncertainties in RCM estimates for the hindcast period are systematic, and therefore exist in future projections, DF were applied to projected future climate change data. The same assessments made of the hindcast estimates were repeated for the future projections. Plots were made for each weather variable at each location for observed and the downscaled future projection.

3.4 Results.

3.4.1 Model estimate evaluation.

3.4.1.1 Precipitation.

The model produces an excess of small (< 0.3 mm) precipitation events (Fig. 4), resulting in a large under-estimation in the number of dry days (0 mm, Table 1). The mean number of dry days for all modelled sites was 67 compared with 163 for observed data.

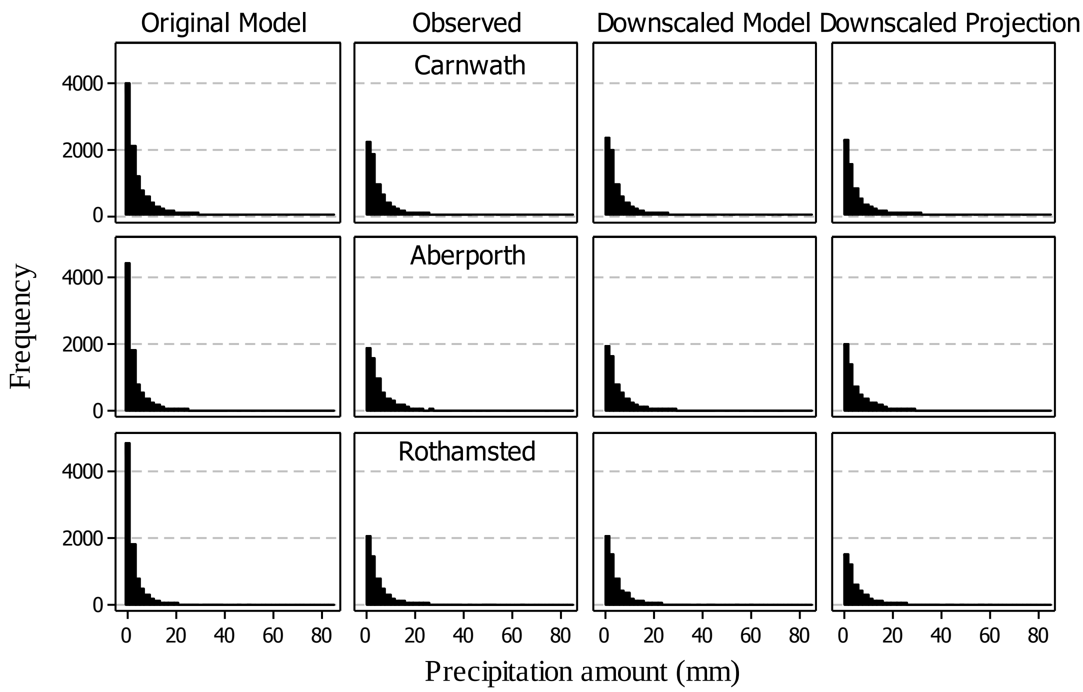


Figure 4. Histograms of HadRM3 modelled hindcast precipitation estimates, observed, downscaled modelled hindcast estimates and downscaled future projections (A2 scenario for 2070-2100) at three selected sites: Carnwath, Aberporth and Rothamsted.

For the mean annual total, the model was able to produce very good estimates at some sites (i.e. Cawood, under-estimated by only 1 mm), but also poor estimates, (i.e. Auchincruive, cell 4694, over-estimated by 662 mm, or Eskdalemuir, cell 4801, under-estimated by 854 mm), under-estimating for ten of the 17 cells assessed (Table 1). Despite over-estimating the number of dry days, the model under-estimated the number of rainfall events in the range of 2 – 30 mm (Fig. 5B and 6B). The differences between observed and modelled data for larger rainfall events are proportionally smaller and have a less significant effect on overall totals than the more frequent small to mid-range events.

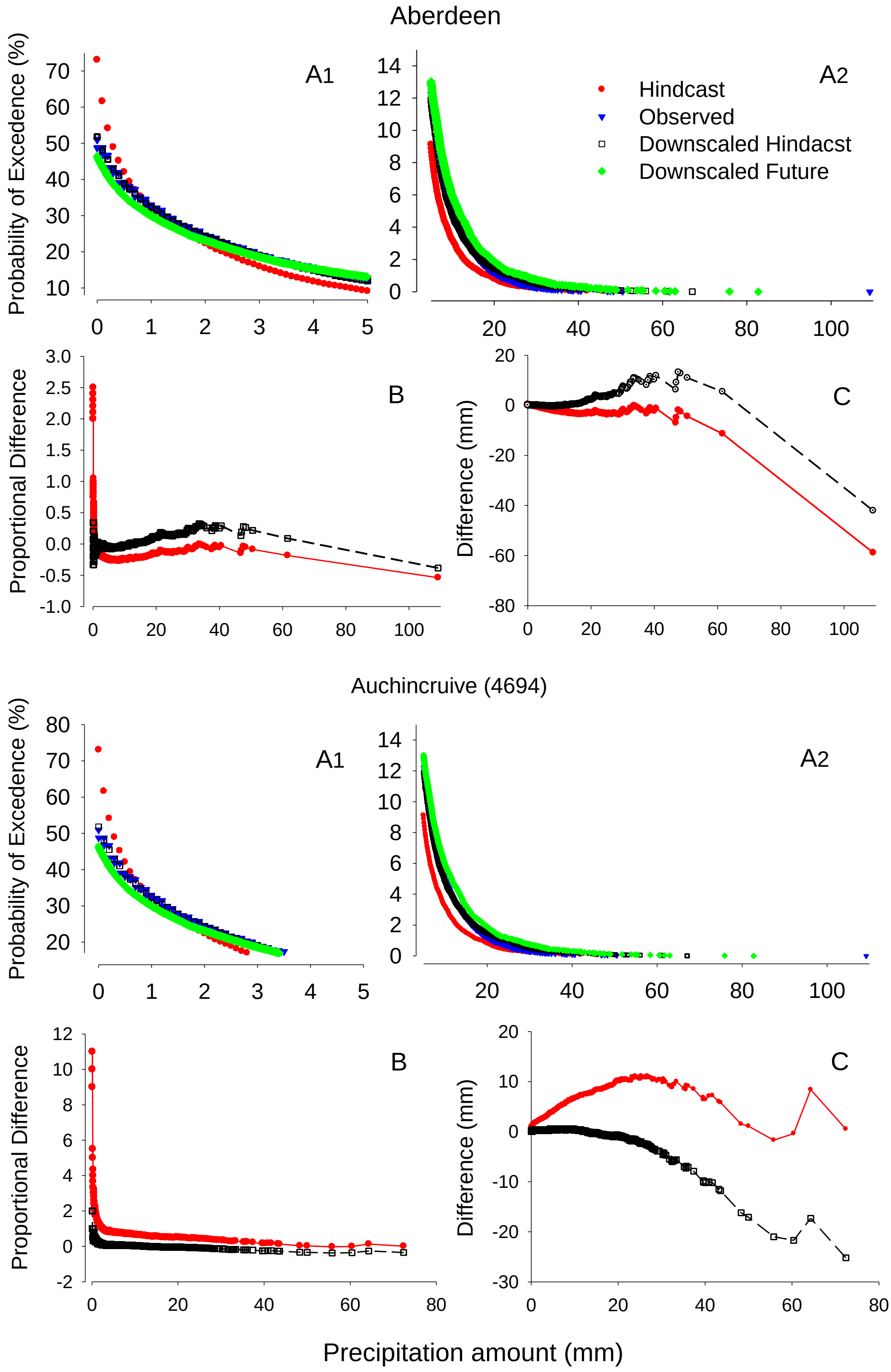


Figure 5 Probability of excedence plots (A) for observed (blue triangles), original model hindcast estimates (red dots) and downscaled model estimates (green squares); proportional difference plots (B) and difference plots (C) for original model hindcast estimates (red dots) and downscaled model estimates (green squares) for Aberdeen and Auchincruive.

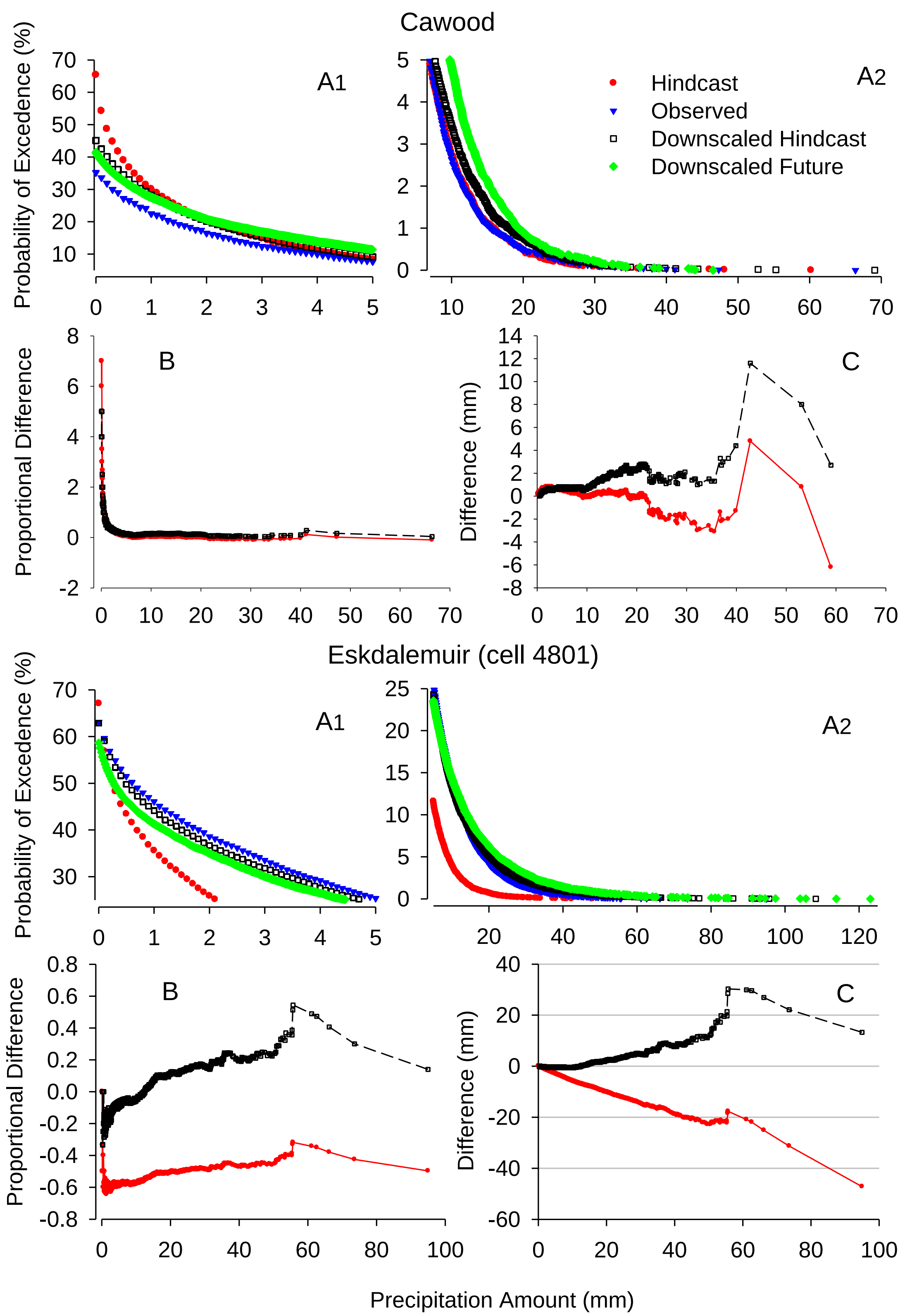


Figure 6. Probability of excedence plots (A) for observed (blue triangles), original model hindcast estimates (red dots) and downscaled model estimates (green squares); proportional difference plots (B) and difference plots (C) for original model hindcast estimates (red dots) and downscaled model estimates (green squares) for Cawood and Eskdalemuir.

Where the model over-estimates the mean annual total, the over-estimation of precipitation events increased asymptotically to a maximum of 10 mm at 23 mm and then decreased towards 0 mm at 50 mm (beyond 50 mm there were insufficient events to discern a consistent pattern). In contrast, where the model under-estimated the mean annual total, there was a near-linear increase in the under-estimation, to a maximum of 22 mm at 50 mm. Where the model performed well, differences were due to the larger observed events.

The model under-estimated the largest single precipitation event at 14 of the 17 cells (observed mean maximum event for all sites was 72 mm compared with a modelled mean of 58 mm). However, only at Mylnefield did the model over-estimate by more than 10 mm (Table 1). The largest single observed event was at Aberdeen (109.2 mm) where the model estimated 50 mm. The largest modelled event was 73 mm. The patterns of mean weekly precipitation (Fig. 7) were replicated well, e.g. Carnwath, Rothamsted, Sutton Bonington.

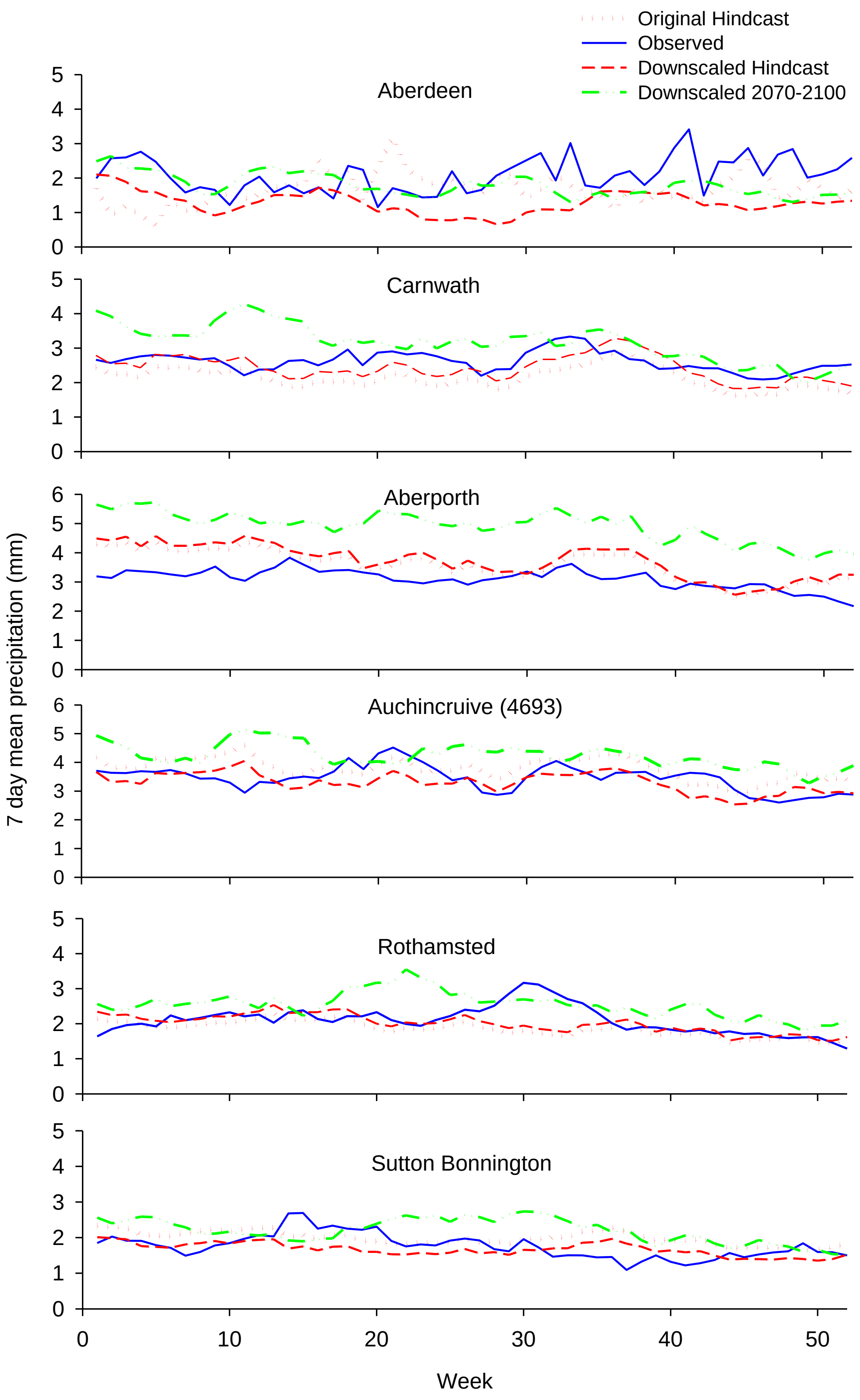


Figure 7. Seven day precipitation mean for observed (solid blue), original HadRM3 hindcast estimates (dotted red), downscaled hindcast estimates (dashed red) and downscaled projected (A2 scenario for 2070-2100) (green dot and dashed).

Table 1. Comparison between observed and modelled (1960-90) precipitation (mm) for mean annual total, maximum (largest) single event and number of days without precipitation (dry days), before and after application of downscaling factors and downscaled A2 scenario 2070-2100 projections (↑ = increase, ↓ = decrease, ≈ = approximately the same).

Meteorological Station	Mean Annual Total (mm)							Maximum single event (mm)				Dry days (0 mm)			
		Before		After		Downscaled			Model		Downscaled		Model		Downscaled
(cell)	Obs	Model	Diff	Model	Diff	projection		Obs	Before	After	projection	Obs	Before	After	projection
Aberdeen (4273)	761	604	-157	731	-30	733	≈	109	50	67	79	173	57	167	195
Aberporth (5434)	870	838	-31	858	-12	921	↑	85	66	72	57	163	76	159	165
Aldergrove (4797)	845	814	-31	833	-12	818	≈	66	49	53	60	130	64	131	153
Auchincruive (4693)	936	1074	138	929	-7	395	↓	72	59	54	34	156	48	148	220
Auchincruive (4694)	936	1597	662	928	-8	1006	↑	72	73	47	47	152	47	147	159
Bracknell (5757)	663	761	98	658	-5	626	↓	71	56	55	50	193	78	190	217
Carnwath (4589)	832	723	-109	817	-15	835	≈	59	64	75	74	135	63	133	159
Cawood (5121)	536	535	-1	550	14	594	↑	66	60	69	45	183	83	193	211
East Malling (5759)	650	547	-103	642	-8	595	↓	82	63	81	66	193	95	190	220
Eskdalemuir (4695)	1534	1215	-319	1514	-21	1552	↑	95	66	87	86	127	48	125	148
Eskdalemuir (4801)	1534	681	-854	1514	-20	1580	↑	95	48	108	121	127	77	125	149
Everton (5862)	738	777	40	732	-6	716	↓	56	55	58	56	203	63	201	224
Lerwick (3639)	1201	1057	-144	1186	-15	1279	↑	59	42	54	74	96	23	103	103
Mylnefield (4484)	692	500	-192	659	-33	665	≈	49	73	102	108	175	79	167	193
Rothamsted (5652)	674	619	-55	666	-7	622	↓	64	50	59	61	178	79	176	210
Sutton Bonington (5333)	601	711	110	598	-3	555	↓	59	50	48	62	191	70	189	215
Wallingford (5650)	577	693	116	574	-3	549	↓	65	61	59	57	204	79	200	225
Mean (all sites)	858	809	-49	846	-11	826	↓	72	58	68	67	163	67	161	186

3.4.1.2 Temperature.

The model estimates *Tmax* well for some times in the year, particularly the spring period (i.e. Aberdeen, Fig. 8), but to over-estimate *Tmin* (i.e. Carnwath and Rothamsted, Fig. 8), although this was not true of all sites. This results in a daily range (*Tmax – Tmin*,) that was too narrow, particularly in the spring and summer (Fig. 12), leading to errors in thermal time accumulation (Fig. 10). The main discrepancies in *Tmax* are under-estimates in the autumn and over-estimates in mid-summer (i.e. Everton, Fig. 8) and at the beginning of the year (i.e. Carnwath, Fig. 8). At Aldergrove, however, the modelled *Tmin* matched the observed values well, but *Tmax* was under-estimated, except in January and February.

Annual mean *Tmax* is generally under-estimated by a small amount (0.30 ºC), but the mean *Tmin* is over-estimated by an average of 0.72 ºC. The model tends to under-estimate annual mean *Tmax* (except at higher elevation sites) by a mean absolute difference of 0.48 ºC, whilst over-estimating *Tmin* (conversely, except at most coastal sites) by a mean absolute difference of 1.06 ºC (Table 2).

The highest *Tmax* values were over-estimated at 14 of the 17 cells (observed mean for all sites was 30.7 ºC compared with the modelled mean of 34.2 ºC), though at some, e.g. Aldergrove, the estimates were very close. For the lowest estimates of *Tmax*, the model under-estimated by an average of 1.7 ºC, but did not manage to replicate the lower *Tmax* values, i.e. at Carnwath (Table 3). It also under-estimated the mean number of days when the *Tmax* was > 15 ºC by an average of 14 days per year compared against the observed, and for some locations by as much as 35 days (Auchincruive, cell 4694). At Bracknell (Fig. 9), the model over-estimated the highest values of *Tmax* during the summer but under-estimated them in the early spring, whilst there is a very good match for the lowest *Tmax* values.

For *Tmin*, the highest values were over-estimated by an average of 3.6 ºC, but for some locations, e.g. Rothamsted, by as much as 7.5 ºC whilst for Aberdeen it was exactly right (Table 4). The model did not estimate the lowest observed values of *Tmin* well (Fig. 9), being on average 5.9 ºC lower than the hindcasts (Table 4). Generally, *Tmin* did not match those of the observed mean daily temperatures in the winter period. The lowest observed *Tmin* value of -24.8 ºC was at Carnwath, where the model estimated -12.0 ºC. The total number of days below 0 ºC in some locations and over-estimated in others. Deviations ranged from 38 days too few (Carnwath) to 31 days too many (Everton). A similar pattern is seen in the estimates of days below -5 ºC, with under- and over-estimates of -19 days (Carnwath) and +17 days (Everton).

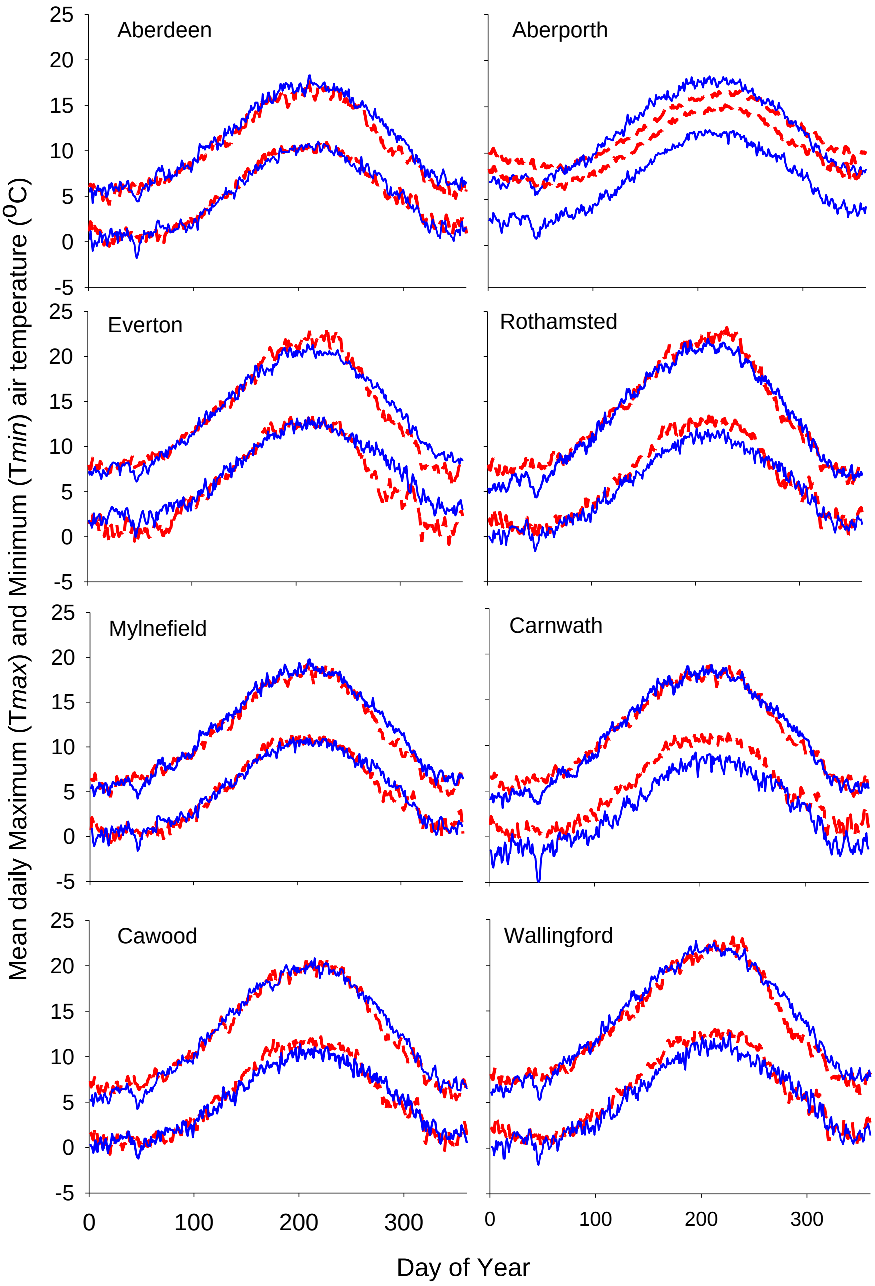


Figure 8: Modelled (red dashed line) versus observed (blue solid line) mean daily maximum (*Tmax* upper lines) and minimum (*Tmin* lower lines) air temperature from eight selected sites.

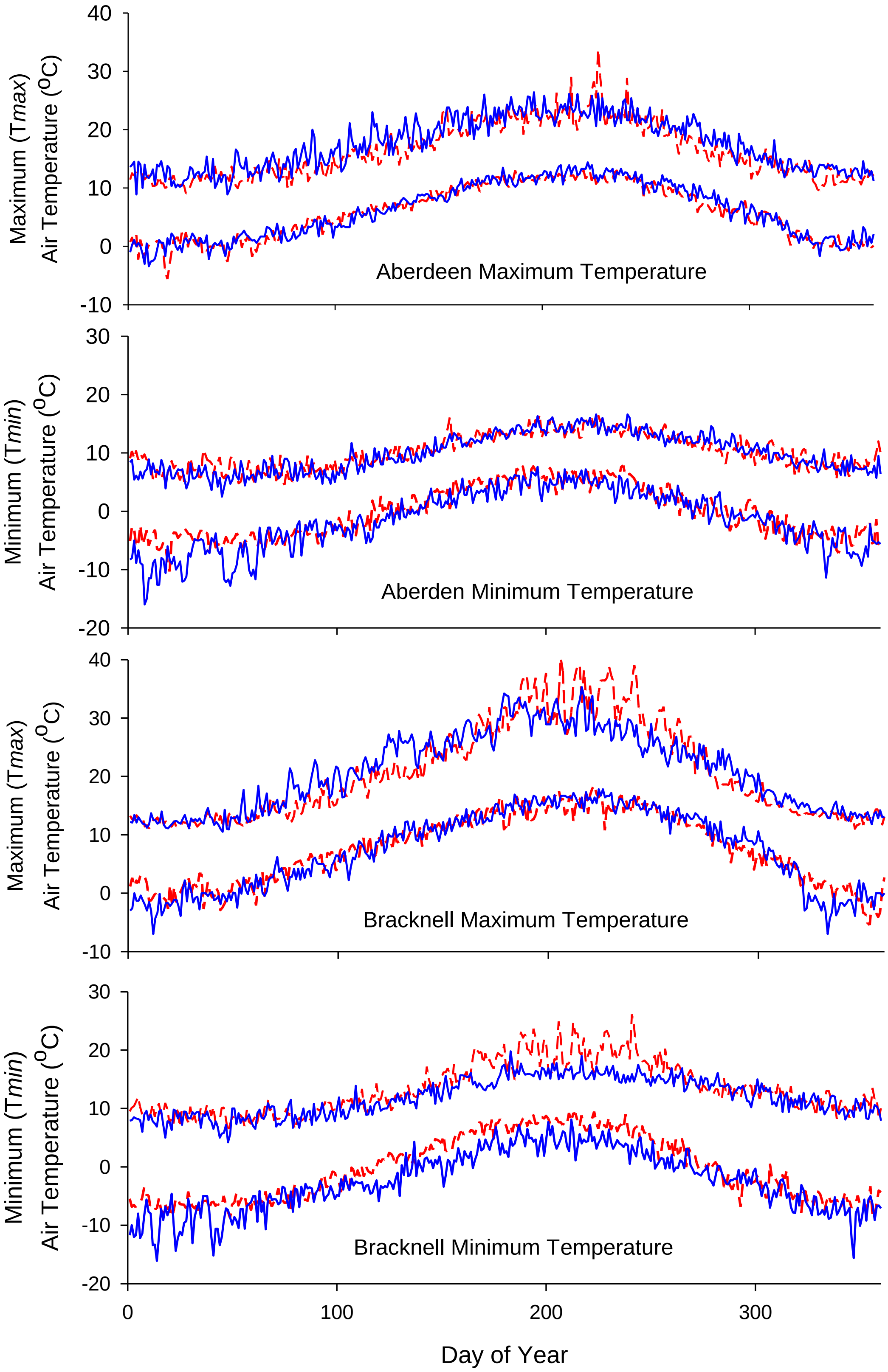


Figure 9. Highest (upper lines) and lowest (lower lines) of maximum (*Tmax*) air temperature and highest (upper lines) and lowest (lower lines) of minimum (*Tmin*) air temperature values for modelled hindcast 1961-1990 (red dashed line) versus observed (blue solid line) data.

Table 2. Mean annual *Tmax* and *Tmin* (ºC) for observed (Obs), original HadRM3 hindcast, downscaled hindcast estimates and downscaled model A2 2070-2100 projections.

Meteorological station (Cell)	Mean Annual *Tmax (ºC)*						Mean Annual *Tmin (ºC)*					
	Obs	Original hindcast	Diff (Orig-Obs)	D'scaled hindcast	Diff (DM-Obs)	D'scaled Projection	Obs	Original hindcast	Diff (Orig-Obs)	D'scaled hindcast	Diff (DM-Obs)	D'scaled Projection
Aberdeen (4273)	11.12	10.46	-0.66	11.12	0.00	14.07	4.83	4.95	0.12	4.83	0.00	7.60
Aberporth (5434)	12.16	12.12	-0.05	12.16	0.00	14.57	6.92	10.31	3.39	6.92	0.00	9.41
Aldergrove (4797)	12.38	11.70	-0.68	12.38	0.00	15.17	5.57	5.75	0.18	5.57	0.00	8.17
Auchincruive (4693)	11.99	11.22	-0.77	11.99	0.00	16.93	5.55	4.66	-0.90	5.55	0.00	9.57
Auchincruive (4694)	11.99	10.52	-1.47	11.99	0.00	15.00	5.55	4.57	-0.99	5.55	0.00	8.47
Bracknell (5757)	13.88	13.55	-0.33	13.88	0.00	18.28	5.44	6.19	0.75	5.44	0.00	9.12
Carnwath (4589)	11.12	11.19	0.07	11.12	0.00	14.31	2.87	4.95	2.08	2.87	0.00	5.85
Cawood (5121)	13.01	12.42	-0.58	13.01	0.00	16.52	5.21	5.34	0.13	5.21	0.00	8.90
East Malling (5759)	14.09	13.99	-0.09	14.09	0.00	18.28	6.05	6.97	0.92	6.05	0.00	9.79
Eskdalemuir (4695)	10.79	10.46	-0.34	10.79	0.00	13.98	3.38	4.52	1.14	3.38	0.00	6.30
Eskdalemuir (4801)	10.79	11.53	0.74	10.79	0.00	14.08	3.38	4.40	1.02	3.38	0.00	6.66
Everton (5862)	13.81	13.72	-0.09	13.81	0.00	18.10	6.81	5.80	-1.01	6.81	0.00	10.76
Lerwick (3639)	9.22	9.49	0.27	9.22	0.00	11.13	4.71	8.28	3.56	4.71	0.00	6.68
Mylnefield (4484)	11.84	11.41	-0.43	11.84	0.00	15.05	5.03	5.01	-0.02	5.03	0.00	8.05
Rothamsted (5652)	13.21	13.66	0.45	13.21	0.00	17.50	5.32	6.21	0.89	5.32	0.00	8.97
Sut'n Bonington (5333)	13.32	12.65	-0.67	13.32	0.00	17.31	5.48	5.59	0.11	5.48	0.00	8.85
Wallingford (5650)	14.03	13.53	-0.50	14.03	0.00	18.33	5.28	6.11	0.82	5.28	0.00	8.89
Mean	12.28	11.98	-0.30	12.28	0.00	15.80	5.14	5.86	0.72	5.14	0.00	8.36
Absolute Difference			5.13		0.00				12.22		0.00	
Mean absolute difference			0.48		0.00				1.06		0.00	

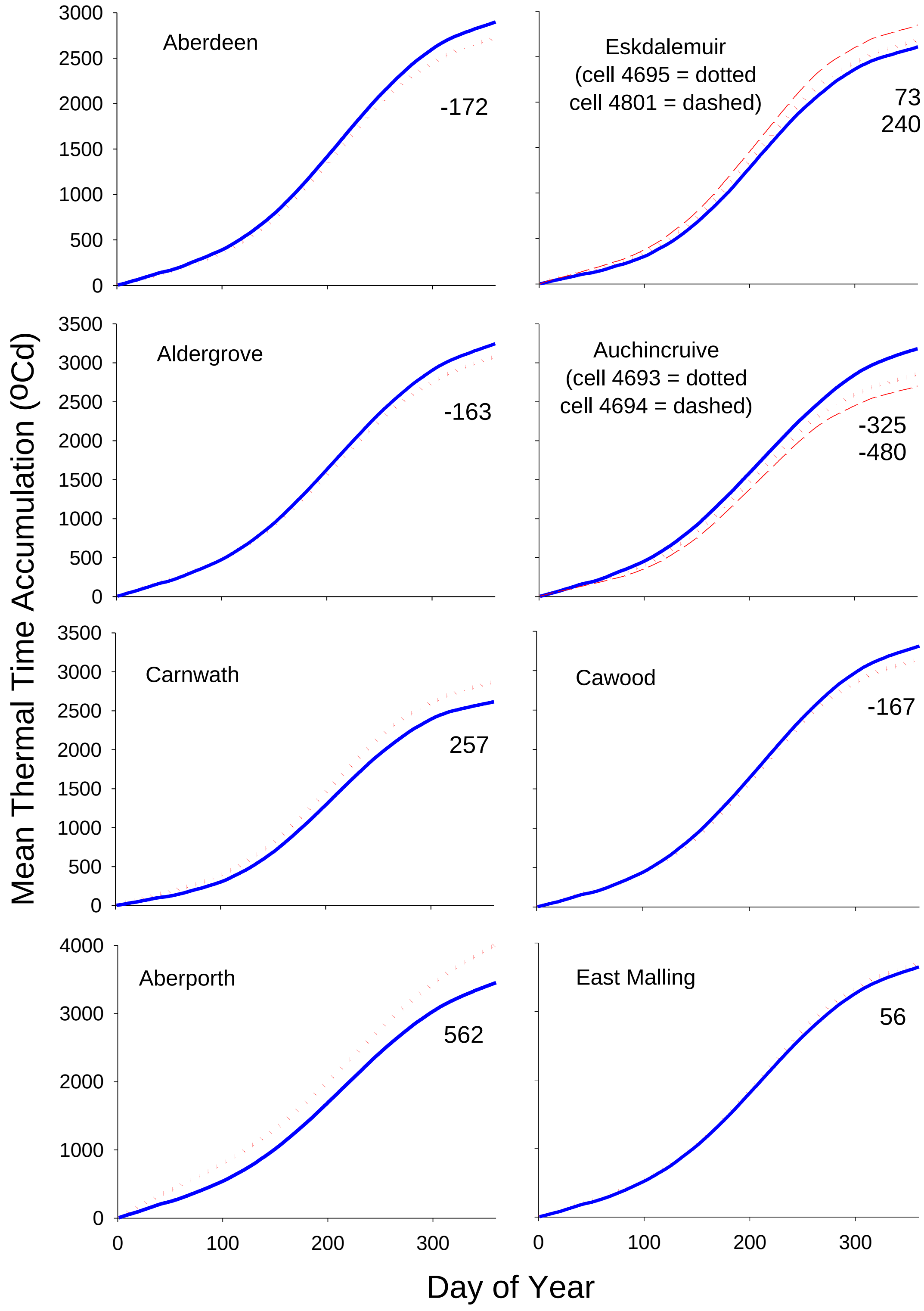


Figure 10. Mean thermal time accumulation (°Cd) for modelled hindcast (red dashed line) and observed (blue solid line) data. Values are the difference between modelled and observed mean thermal time accumulation on day 360.

Table 3. Comparison between observed and modelled (1960-90) maximum temperature (*Tmax* ºC) for highest and lowest single value, and the number of days > 15 ºC before and after application of downscaling factors, and downscaled A2 scenario 2070-2100 projections.

Meteorological station (Cell)	Highest single value (deg C)				Lowest single value (deg C)				Mean Days >15 deg C			
		Model		Downscaled		Model		Downscaled		Model		Downscaled
	Obs	Before	After	projection	Obs	Before	After	projection	Obs	Before	After	projection
Aberdeen (4273)	26	34	34	37	-3	-6	-5	1	86	70	72	155
Aberporth (5434)	32	23	24	27	-5	1	0	3	106	82	97	170
Aldergrove (4797)	25	24	33	39	0	1	-2	1	121	93	123	180
Auchincruive (4693)	29	32	33	47	-3	-8	-7	2	107	88	105	202
Auchincruive (4694)	29	31	33	39	-3	-6	-6	1	107	72	110	176
Bracknell (5757)	35	40	41	47	-7	-5	-5	1	156	138	153	213
Carnwath (4589)	30	35	35	42	-12	-3	-4	0	96	94	101	166
Cawood (5121)	34	39	39	46	-5	-4	-4	2	141	121	142	198
East Malling (5759)	35	41	41	47	-6	-6	-5	2	160	146	158	219
Eskdalemuir (4695)	30	34	34	42	-10	-6	-7	-1	85	76	89	157
Eskdalemuir (4801)	30	35	34	42	-10	-6	-6	-1	85	104	86	157
Everton (5862)	34	39	38	47	-5	-7	-8	0	151	141	151	219
Lerwick (3639)	22	16	17	20	-3	-1	-3	1	17	1	8	54
Mylnefield (4484)	29	36	37	41	-9	-3	-3	0	112	101	112	176
Rothamsted (5652)	34	41	40	47	-7	-6	-6	0	145	141	142	204
Sutton Bonington (5333)	35	40	41	48	-7	-5	-4	1	144	125	145	206
Wallingford (5650)	35	41	41	47	-9	-5	-4	1	158	137	156	215
Mean	31	34	35	41	-6	-4	-5	1	116	102	115	180

Table 4. Difference between observed and modelled (1960-90) minimum temperature (*Tmin* ºC) for highest and lowest single value, and the number of days < 0 ºC and < -5 ºC before and after application of downscaling factors and downscaled A2 scenario 2070-2100 projections.

Meteorological Station (cell)	Highest single value (deg C)				Lowest single value (deg C)				Mean Days < 0 deg C				Mean Days < -5 deg C			
	Obs	Model Before	Model After	D'scaled Project'n	Obs	Model Before	Model After	D'scaled Project'n	Obs	Model Before	Model After	D'scaled Project'n	Obs	Model Before	Model After	D'scaled projection
Aberdeen (4273)	17	17	17	23	-16	-10	-11	-6	55	53	59	10	7	2	2	0
Aberporth ((5434)	20	19	16	21	-10	-1	-5	-1	21	0	11	0	1	0	0	0
Aldergrove (4797)	18	20	19	22	-11	-8	-8	-6	44	40	46	9	4	2	3	0
Auchencruive (4693)	18	20	21	29	-13	-14	-13	-6	47	72	57	11	6	21	14	0
Auchencruive (4694)	18	19	20	23	-13	-12	-11	-7	40	70	54	17	5	14	8	1
Bracknell (5757)	20	26	25	32	-16	-9	-9	-8	62	53	60	16	9	7	10	1
Carnwath (4589)	18	19	17	21	-25	-12	-14	-10	103	65	105	43	28	9	26	5
Cawood (5121)	18	23	23	27	-15	-10	-10	-5	53	62	60	8	6	7	7	0
East Malling (5759)	19	25	24	30	-18	-8	-8	-5	48	41	50	9	5	2	4	0
Eskdalemuir (4695)	16	19	18	22	-19	-13	-13	-9	89	72	91	33	17	13	18	3
Eskdalemuir (4801)	16	20	18	23	-19	-13	-13	-9	89	81	93	34	17	19	22	3
Everton (5862)	19	26	26	34	-11	-15	-14	-9	37	68	49	12	3	20	9	1
Lerwick (3639)	14	15	12	14	-8	-3	-8	-2	45	0	27	1	2	0	0	0
Mylnefield (4484)	18	20	20	22	-17	-9	-9	-6	54	64	62	19	7	4	5	0
Rothamsted (5652)	18	26	25	31	-17	-9	-9	-8	57	53	62	17	7	6	10	0
Sutton Bonington (5333)	18	24	24	31	-16	-10	-10	-7	53	58	56	14	8	7	7	0
Wallingford (5650)	19	26	25	31	-21	-9	-10	-8	62	53	62	18	11	7	11	1
Mean	18	21	20	26	-16	-10	-10	-7	56	53	59	16	8	8	9	1

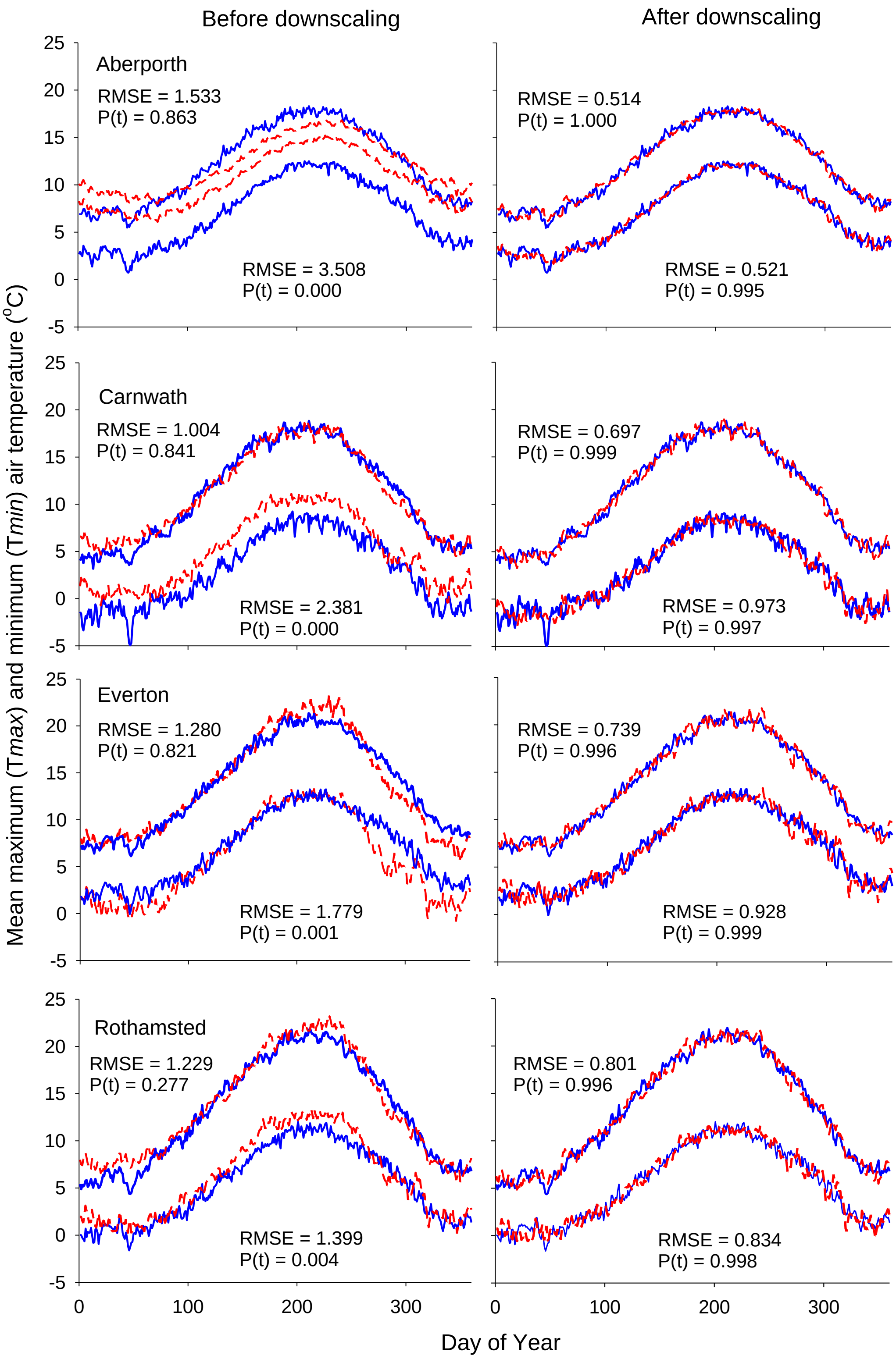


Figure 11. Comparison of improvement in data quality before downscaling of HadRM3 estimates (dashed red) of *Tmax* (upper lines) and *Tmin* (lower lines) and observed (solid blue) after application of Monthly downscaling factors at four examples sites. RMSE is the Root Mean Square Error in ºC, and P(t) is the 2 tailed paired t-test probability of means being equal, where 1 is very high probability).

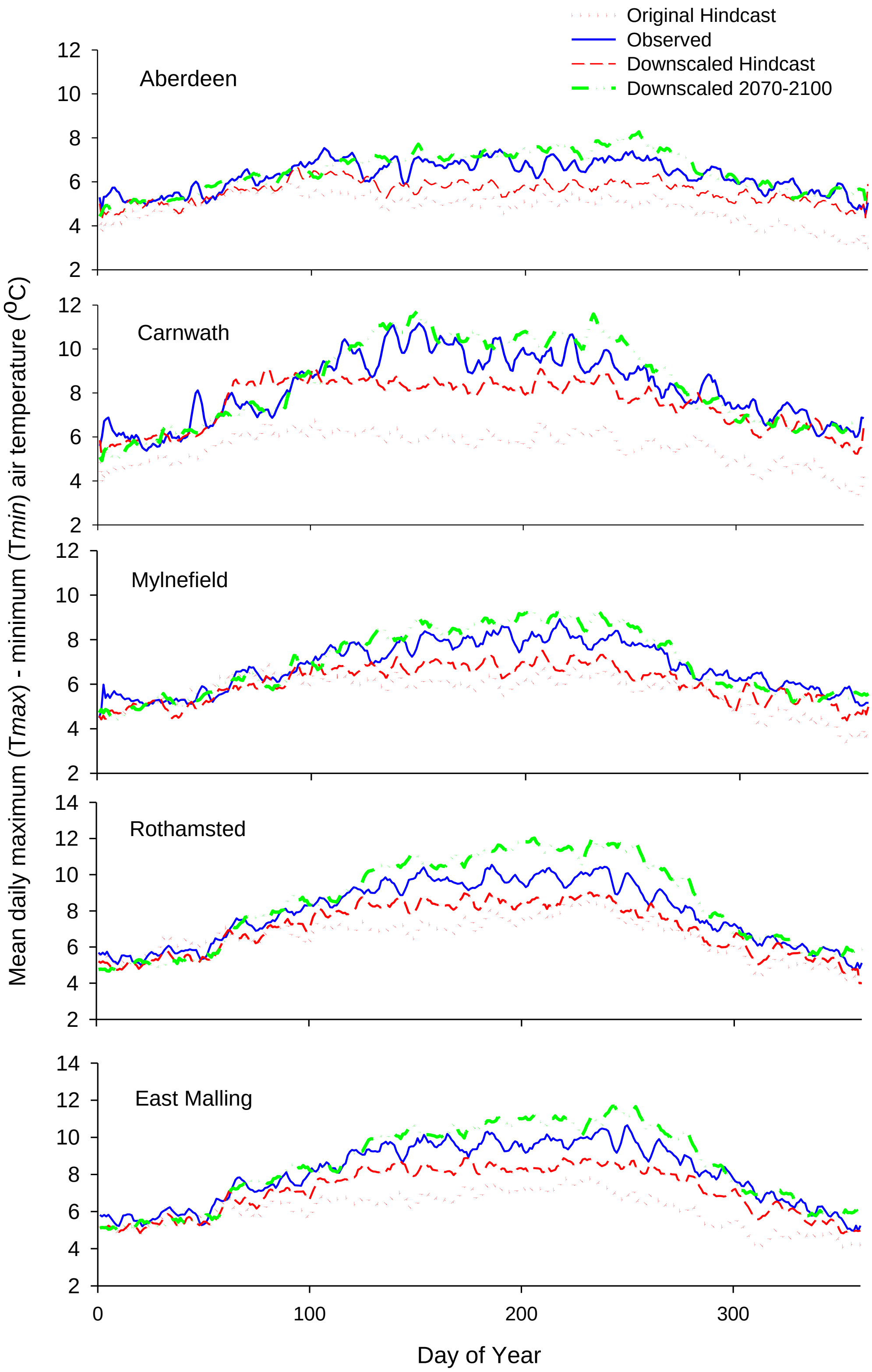


Figure 12. *Tmax* – *Tmin* comparisons for observed (solid blue), original HadRM3 (dotted red), downscaled HadRM3 (dashed red) and downscaled projected A2 scenario 2070-2100 (dot-dashed green) at five example sites.

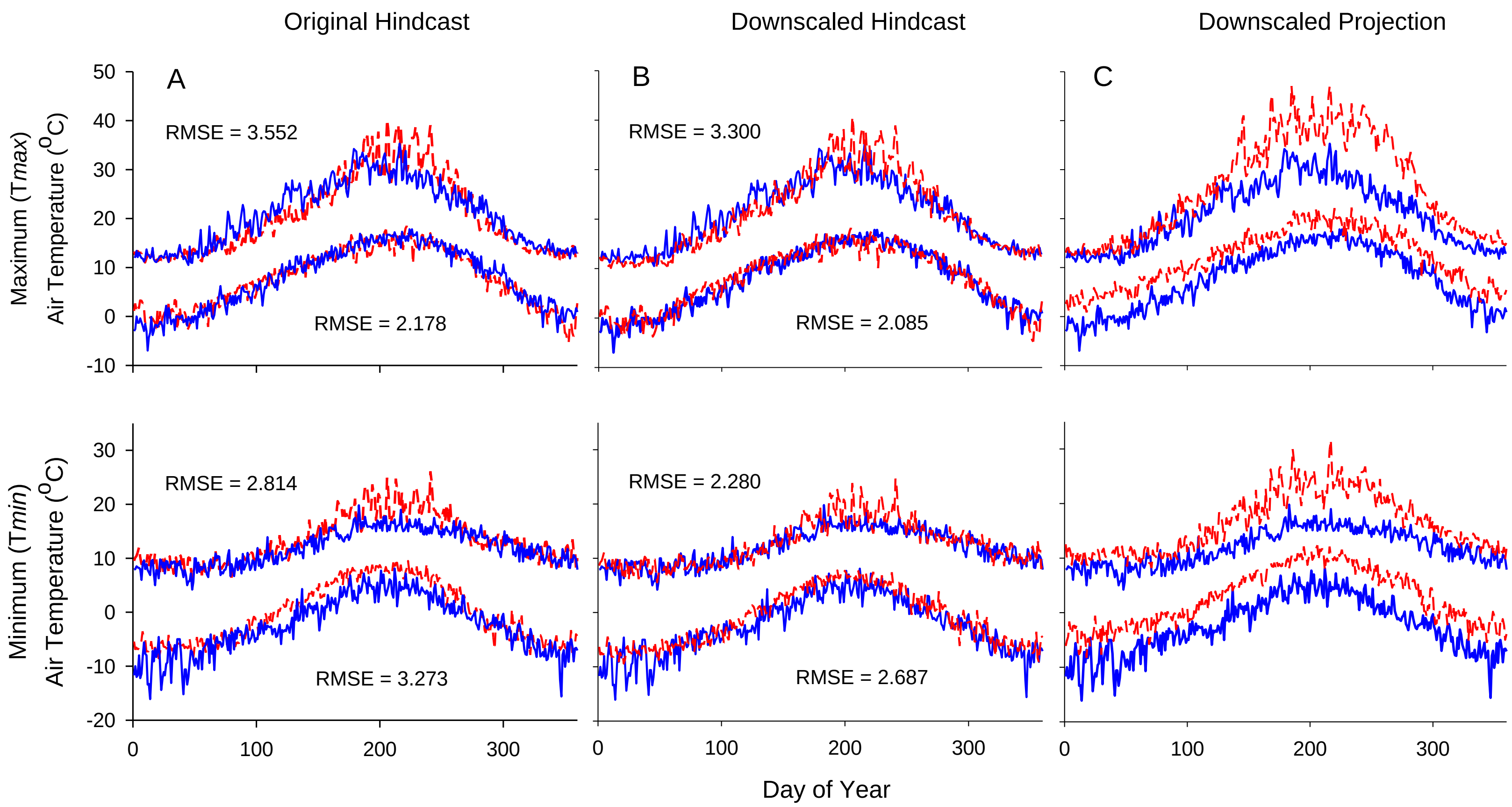


Figure 13. Comparison of observed (solid blue) and HadRM3 original hindcast (A), downscaled hindcast (B) and downscaled projection (A2 for 2070-2100) (C) estimates (dashed red) of the highest values (upper lines) and lowest values (lower lines) of *Tmax* and *Tmin* for Bracknell (cell 5757). RMSE is the Root Mean Square Error in ºC.

For the highest *Tmin* values, the model over-estimated in the summer but showed a good match throughout the rest of the year. The modelled lowest *Tmin* values did not represent well the extreme observed lows at many sites, i.e. Bracknell (Fig. 9) and the spring and summer values were generally over-estimated.

Generally the temporal distribution of mean daily *Tmax* and *Tmin* is modelled adequately, based on the synchronisation of temporal distributions seen in Fig. 8. Data from meteorological stations on the boundary between two cells (Auchincruive and Eskdalemuir) show contrasting results with their corresponding two modelled cells' data. For example, Auchincruive (cells 4693 and 4694) showed similar temperature results (Tables 2, 3 and 4), but a marked difference in precipitation (mean annual totals of 1074 mm and 1597 mm, respectively, Table 1). Hence care has to be taken in deciding which cells' data are most representative of sites on cell boundaries.

3.4.1.3 Solar radiation.

The model systematically over-estimated S_o (i.e. Aberporth, Fig. 14). It does, however, perform well at some locations, e.g. Aberdeen, where the distribution of estimate errors is similar to that from data derived from specialist radiation estimation models. Estimates at sites such as Aberdeen were only about ± 1 MJ m^{-2} day^{-1} larger than those from specialist models, but are much larger at other locations, e.g. Eskdalemuir (cell 4801), where the mean error was 2.02 MJ m^{-2} day^{-1} and the largest single error was 11.2 MJ m^{-2} day^{-1}. The model over-estimated S_o particularly in the late summer to autumn period, when actual values are likely to be high, but there is a shift back towards either accuracy or under-estimation in the spring to early summer period (e.g. East Malling, Everton, Rothamsted and Sutton Bonington, Fig. 14). This indicates a possible systematic model bias.

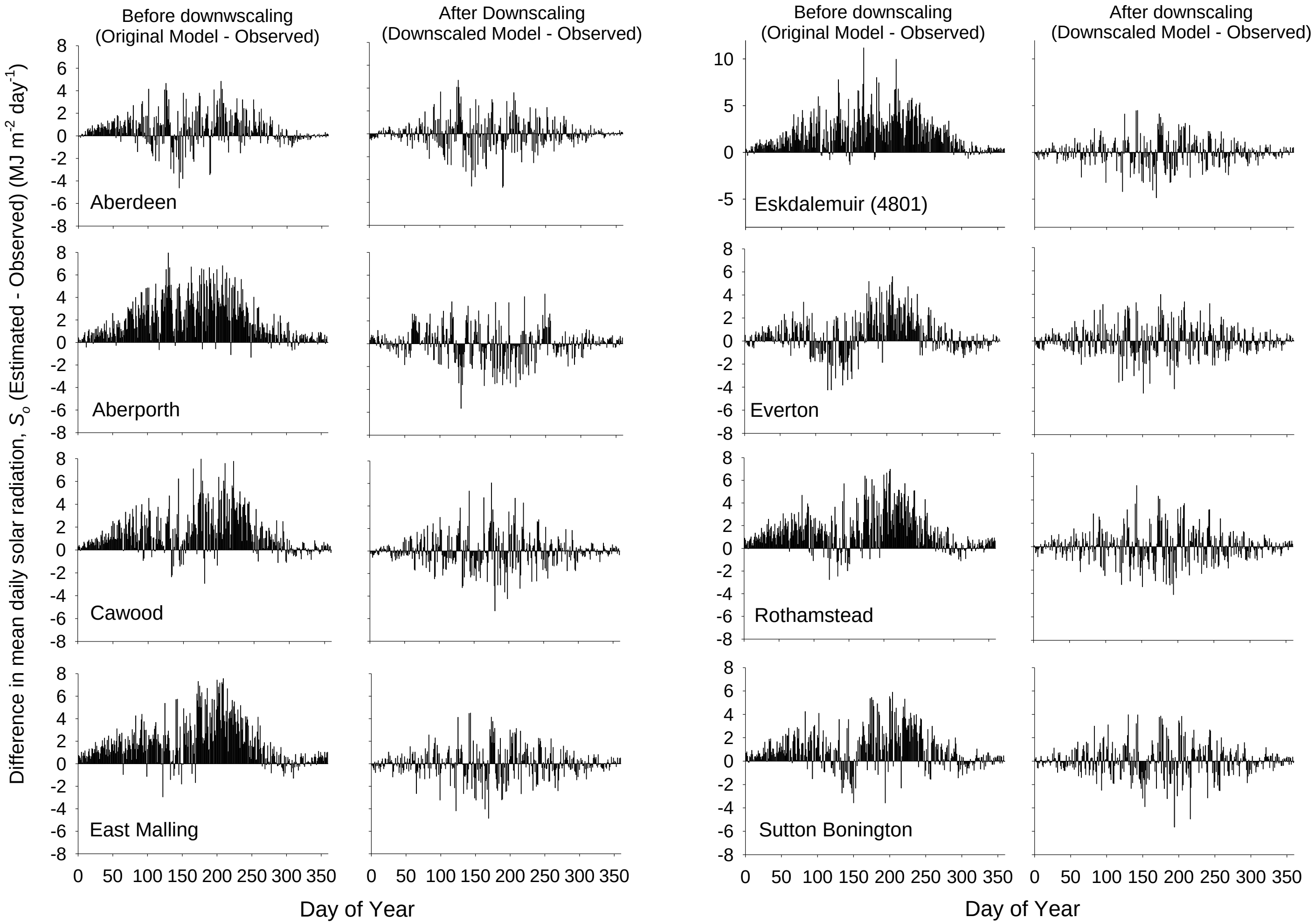


Figure 14. Comparison in improvements in data quality for HadRM3 original hindcast solar radiation (S_o) (modelled – observed mean daily S_o) before and after application of Monthly downscaling factors at eight example sites.

3.4.2 Model estimate downscaling.

3.4.2.1 Precipitation.

The DF_d and DF_{mat} produced downscaled hindcast model data that visually match the observed data very well. The many low magnitude (generally < 0.3 mm) modelled precipitation events were removed (Figs. 4, 5 and 6), resulting in better agreement in the number of dry days (Table 1), with the modelled mean for all sites being 161 (was 67) compared with the observed 163. The largest difference in the number of dry days was only 10, at Cawood. The mean annual total match was improved at all locations, except Cawood, where the model's original estimates were already very good (Table 1). DF_d and DF_{mat} resulted in the modelled estimates of mean annual precipitation (except Cawood) being under-estimated, but by a mean across all sites of only 11 mm. At Eskdalemuir (cell 4801) the model originally under-estimated by 854 mm, but after downscaling the difference was only 20 mm with an error of 2 dry days, whilst also seeing a substantial improvement in the largest single event estimate (observed = 95 mm, hindcast = 48 mm, downscaled projection = 108 mm). However, at only nine of the 17 cells did the DF_d and DF_{mat} improve the estimates of the largest precipitation events. The worst case for this is found at Mylnefield, where the model originally over-estimated the largest precipitation amount (observed = 49 mm, hindcast = 73 mm, downscaled projection = 102 mm).

The difference (ranked observed – modelled) shows that the DF maintains a closer match for the more frequent low to mid-range precipitation events (Figs. 5C and 6C), whilst minimising the proportional difference (Figs. 5B and 6B). There was a mixed response of the seven day mean precipitation (Fig. 7), where the DF appear to improve the match at some locations (i.e. Rothamsted and Auchincruive, cell 4693), but not at others (i.e. Aberporth).

3.4.2.2 Temperature.

Application of monthly DF_{Tmax} and DF_{Tmin} resulted in substantial improvements in the match between observed and downscaled model mean daily *Tmax* and *Tmin* (Fig.11). Most notable is the improvement in *Tmin*, illustrated by Carnwath, giving a better representation of daily temperature range (*Tmax* – *Tmin*) (Fig. 12), although still not ideal in the growing season. However, the downscaled data still did not represent the extreme cold events well, or reduce enough the model's over-estimation of the highest values of *Tmax* in summer (Fig. 13B).

The estimates of annual mean of *Tmax* and *Tmin* were improved at all sites (Table 2), with *Tmin* being seen to improve the most (the mean difference in observed – hindcast data for all sites was 0.3 ºC for *Tmax*, and 0.72 ºC for *Tmin* with both becoming 0.00 ºC after downscaling). For *Tmax*, the downscaled model data still showed an over-estimation of the highest single event (Table 3), actually worsening by 0.8 ºC from the hindcast for the mean for all sites, and multiple high events in the summer (Fig. 13B). There was an improvement in the number of days per year estimated to be > 15 ºC (observed mean for all sites = 116, downscaled modelled mean = 115). For *Tmin*, there was little change in the estimates of the lowest temperature events, but a slight improvement in the highest events (Table 4). Generally the downscaled data better represent the number of days < 0 ºC, but are noticeably better for days < -5 ºC (i.e. Carnwath observed = 28 days, original model = 9 days, downscaled modelled data = 26 days).

3.4.2.3 Solar radiation.

DF_{sr} greatly improved the quality of estimates (Fig. 14), but while not eliminating the errors, resulted in them being evenly distributed about a more realistic mean value. In crop modelling for example, getting the mean value correct is more important than tracking the day-to-day changes, as compensating errors can result in a balance about the mean. DF_{sr} does, however, reduce the seasonal bias seen in the hindcast estimates (under-estimating in late spring to early summer, i.e. Everton and Sutton Bonington), giving a more even temporal distribution of over- and under-estimations. The magnitude of the errors, approximately 4 MJ m^2 day^{-1}, is comparable with those associated with specialised solar radiation estimation models. Therefore the downscaled estimates for S_o can be seen as being of good quality.

3.4.3 Downscaled future estimates.

The differences between observed conditions and future projections can be better evaluated given knowledge of the performance of the model in making the hindcast estimates (i.e. identifying systematic errors), and interpreting the impacts (improvements and continuing inadequacies) of using the DF.

3.4.3.1 Precipitation.

Downscaled future projections for the A2 scenario show a substantial increase in the number of dry days (mean of 23 days) at all locations, but a varied response in the change in mean annual total (Table 1). In six cells the annual total is projected to rise, at four there is little change, but at seven a decrease is projected. The decreases are predominantly in drier locations. Figure 4 indicates that where decreases in mean annual total are projected, i.e. Rothamsted (Table 1) this would be due to a reduction in the number of lower magnitude (< 4mm) precipitation events.

3.4.3.2 Temperature.

Downscaled estimates indicate a substantial warming at all locations tested (Figs. 15B and 16) where mean annual *Tmax* for all sites rises by 3.52 ºC, from the observed 12.28 ºC to a projected 15.80 ºC (Table 2). For *Tmin*, the mean annual value rises by 3.22 ºC, from 5.14 ºC to 8.36 ºC, for all sites. Projections for *Tmin* approach what is approximately the current difference between observed *Tmax* – *Tmin* (Fig. 12). However, the evidence presented here shows the model over-estimates the higher ranges of *Tmax* and *Tmin* in the summer period by an average of 3 ºC across all sites before downscaling, and 4 ºC afterwards (Fig. 13 B). Hence the values for the highest single values of *Tmax* and *Tmin* given in Tables 3 and 4 and shown in Fig. 13C should be regarded with caution. The increase in both *Tmax* and *Tmin* appears to be similar, given the downscaled *Tmax* – *Tmin* (Fig. 12) and considering that the mean daily *Tmax* estimates (Fig. 16) may be too high due to distortion arising from the model's over-estimation of the higher *Tmax* values. Allowing for this, the downscaled *Tmax* does increase more than *Tmin* in the summer. The projected data show a substantial increase in the number of days on which *Tmax* > 15 ºC (observed = 116 days, downscaled hindcast = 115, projection = 180) (Table 3).

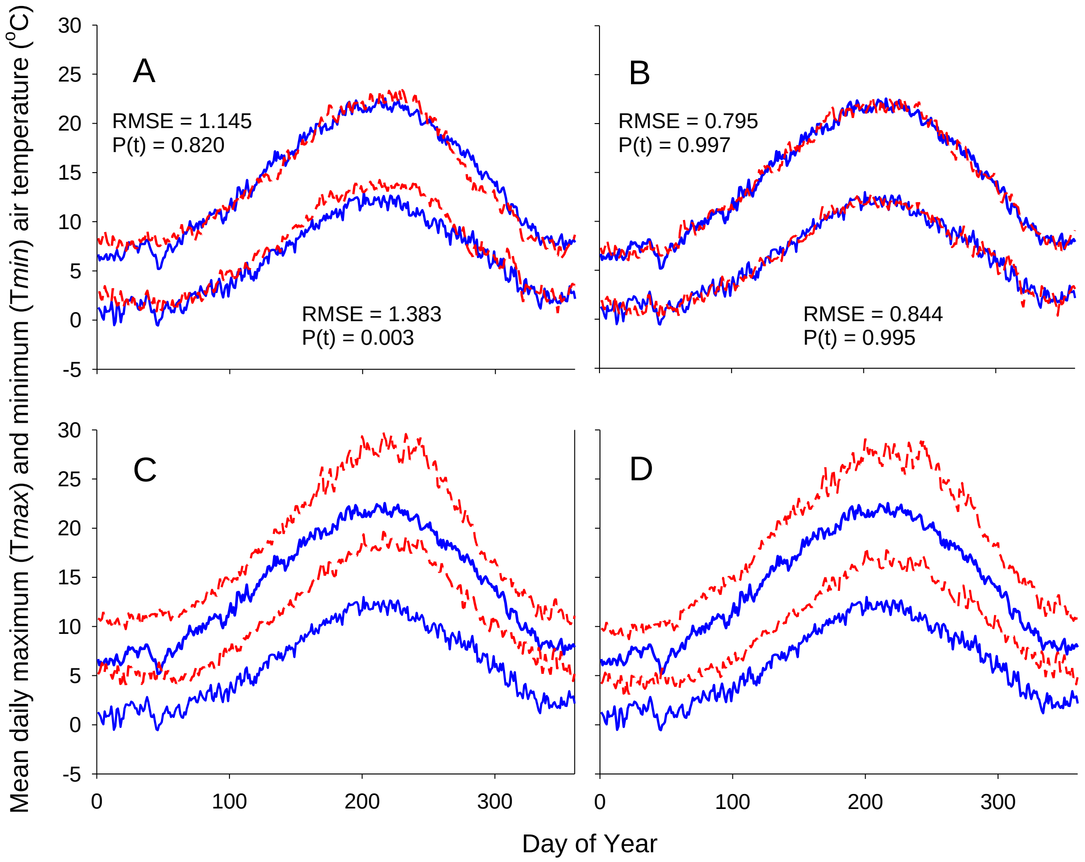


Figure 15. Comparison of *Tmax* and *Tmin* observed (solid blue) and (A) original HadRM3 hindcast, (B) downscaled hindcast, (C) original A2 2070-2100 projected and (D) downscaled A2 2070-2100 projected estimates for East Malling, cell 5759. RMSE is the Root Mean Square Error in ºC, and P(t) is the 2 tailed paired t-test probability of means being equal, where 1 is very high probability).

The model was unable to represent the more extreme cold conditions at some locations, hence the projected values given for the lowest *Tmin* in Table 4 are also questionable. That said, the application of the DF does improve the quality of estimates in terms of the number of days < 0 ºC and <-5 ºC. Therefore greater confidence can be found in the projected number of days below these values, showing there is a substantial decrease in the expected number of cold days.

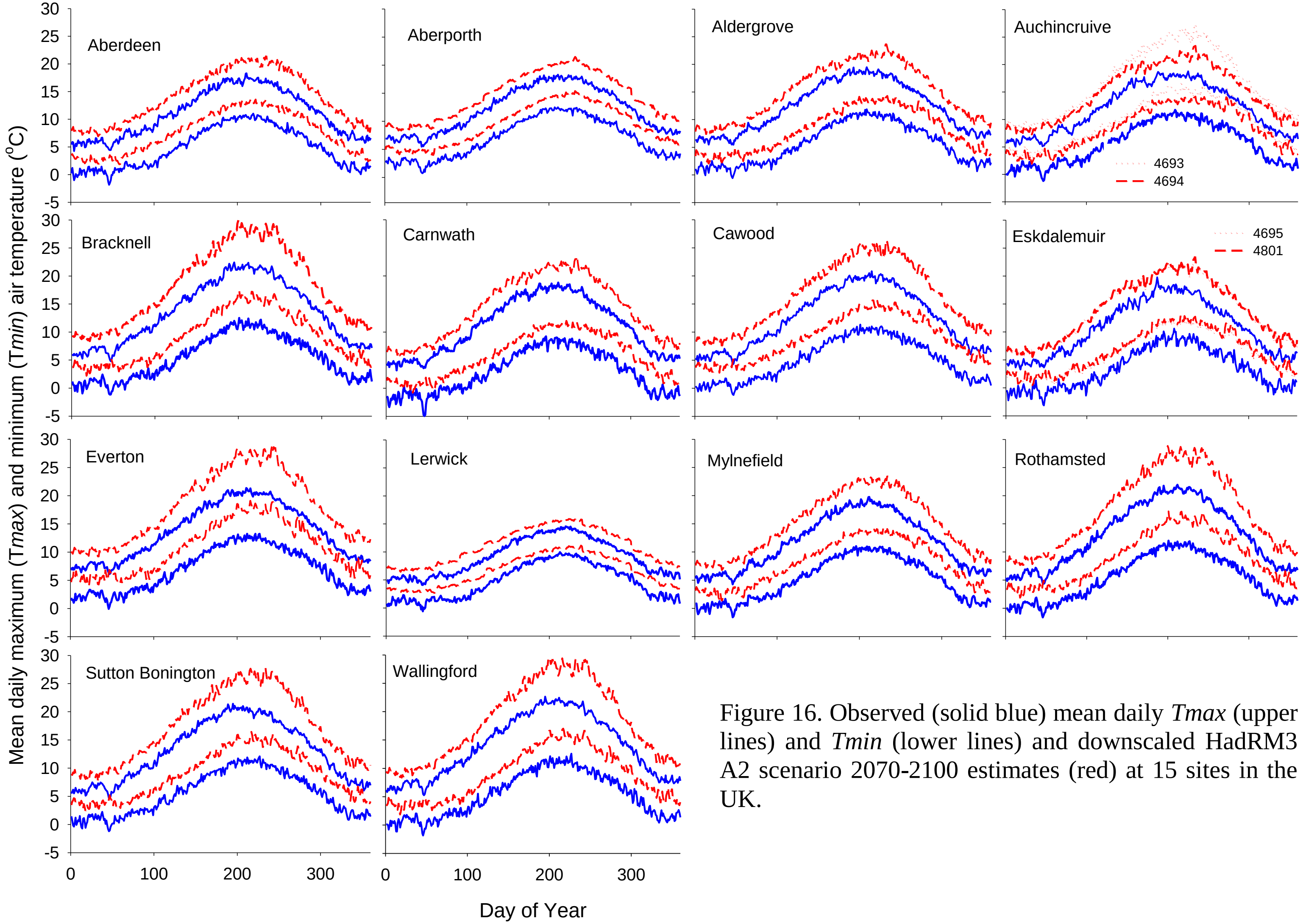


Figure 16. Observed (solid blue) mean daily *Tmax* (upper lines) and *Tmin* (lower lines) and downscaled HadRM3 A2 scenario 2070-2100 estimates (red) at 15 sites in the UK.

3.4.3.3 Solar radiation.

Change may to occur to S_o only in spring to early autumn (May to September), as there is little difference from the observed data outside this period (Figs. 17D and 18). Aberdeen, Aberporth and Aldergrove show very little change, whilst Lerwick's S_o may decrease from mid-summer into winter. Sites in southern UK show the greatest increase in S_o in the summer (i.e. Everton, Rothamsted, Wallingford).

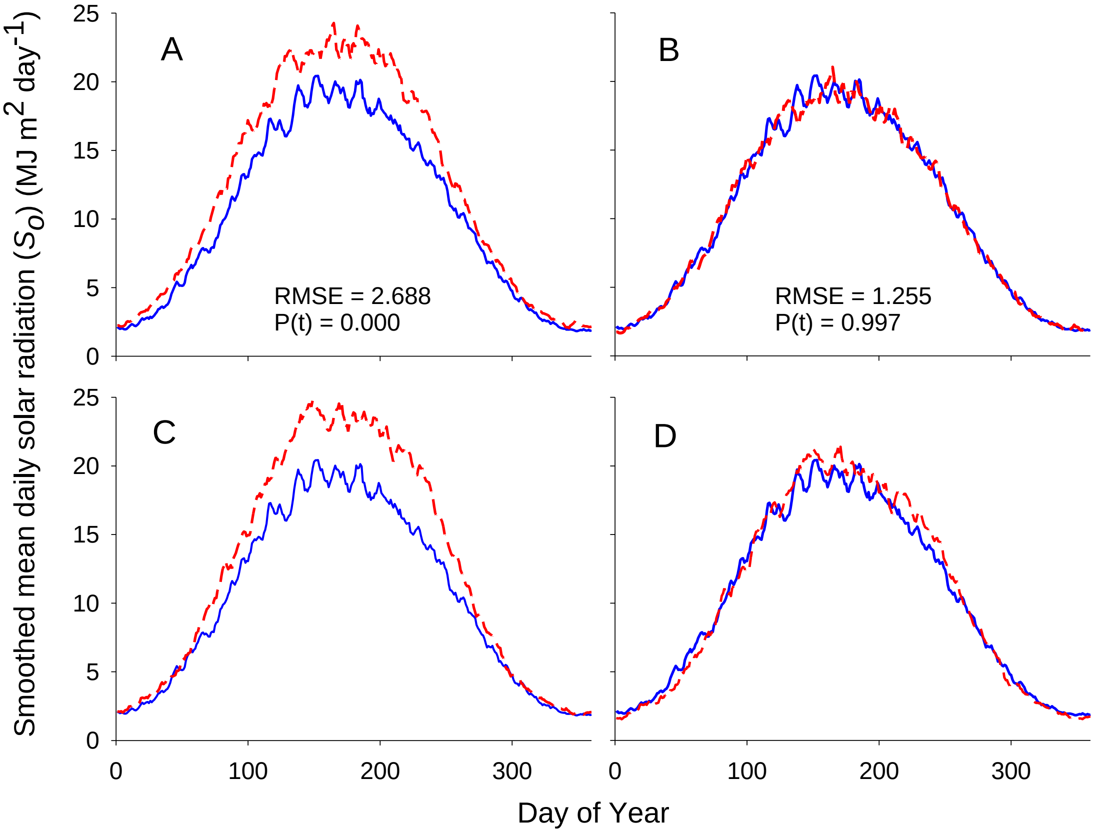


Figure 17. Comparison of smoothed observed (solid blue) and modelled (dashed red) solar radiation (S_o) for (A) original HadRM3 hindcast, (B) downscaled hindcast, (C) original A2 2070-2100 projected and (D) downscaled A2 scenario 2070-2100 projected estimates for Aberporth, cell 5434. RMSE is the Root Mean Square Error in ºC, and P(t) is the 2 tailed paired t-test probability of means being equal (where 1 is very high probability), derived from un-smoothed data.

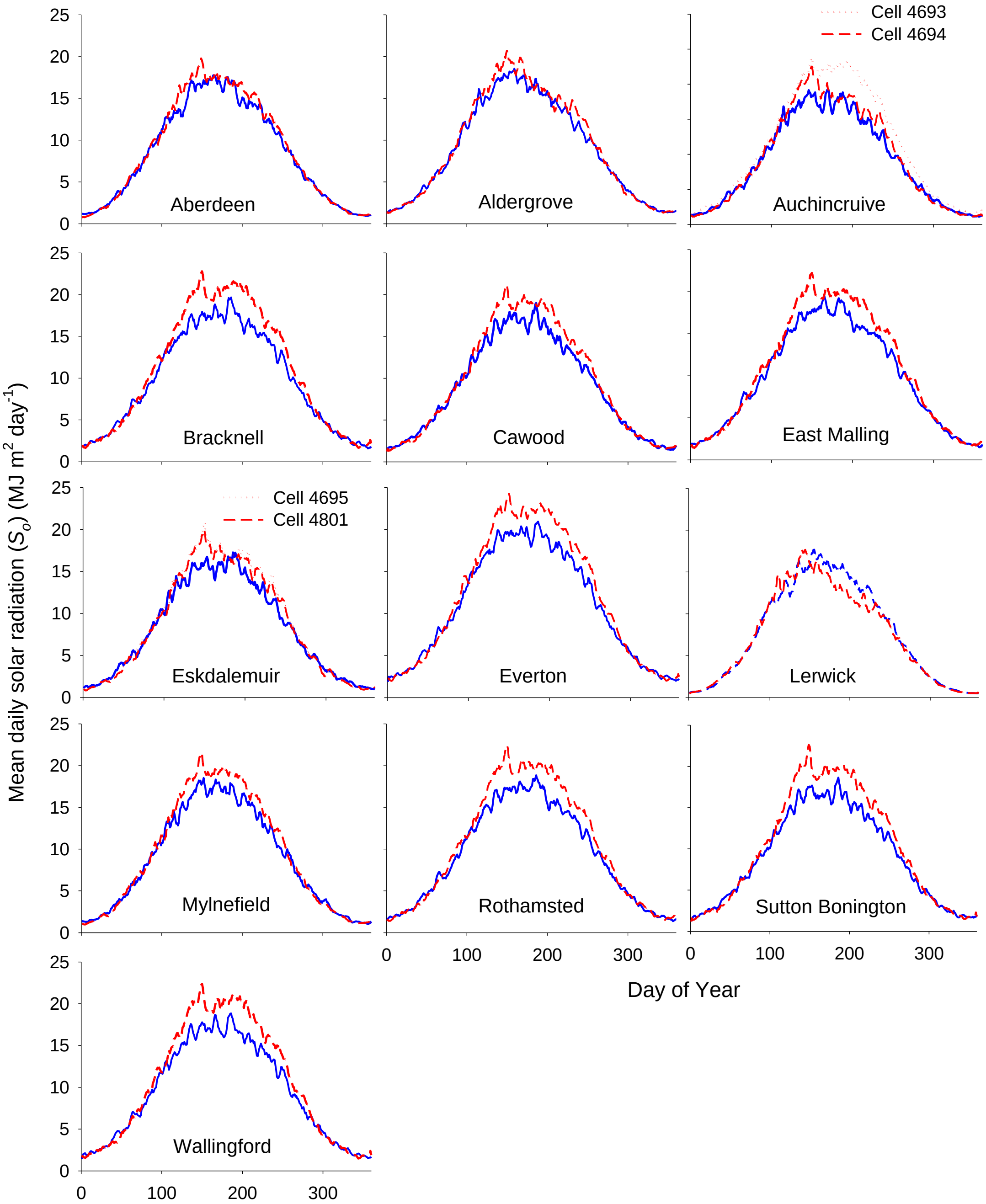


Figure 18. Smoothed observed (solid blue) and downscaled HadRM3 A2 2070-2100 estimates (dashed red) for solar radiation (S_o) at thirteen sites in the UK.

The application of DF$_{sr}$ produces a characteristic 'spike and dip' in the plots of mean daily S_o (Fig. 18) between day 149 and 151 (the transition from May to June). This is due to the model estimating the May S_o well, giving small values for May's DF$_{sr}$, but over-estimating

June's S_o giving a higher DF_{sr}, which is compounded by the smoothing method used to display the results in Fig. 17.

3.5 Discussion.

3.5.1 Model evaluation.

The evaluation of the quality of estimates for the period 1960-90 has implications for the interpretation of future projections of climate change. Assuming that the systematic differences between modelled and observed data occurring within the hindcast estimates are present in the future estimates, then future unadjusted projections of precipitation, extreme summer *Tmax*, mean *Tmin*, lowest *Tmin* and S_o are, at some locations, potentially misleading. However, testing also indicated that mean *Tmax*, the lowest *Tmax* and highest *Tmin* estimates are reliable, requiring minimal downscaling.

The many modelled small precipitation events (< 0.3 mm), without downscaling, may be significant in terms of adversely affecting derived estimates, i.e. evapotranspiration (therefore soil water balance) and crop canopy temperatures (due to increased cooling). These many small events occur due to the model being originally calibrated and validated against spatially aggregated observed data, resulting in a 'drizzle' effect. The fact that the model did not estimate the largest single events does not indicate a failure of the model, but that the thirty year coverage of the hindcast may not be sufficient to capture the more rare extreme events with longer return periods. In conjunction with this, the aim of the model is to represent the mean conditions for a grid cell, rather than specific extreme events recorded at individual stations. However, the consistency with which the model under-estimated the largest single event across all sites does indicate a limitation.

The models' tendency to over-estimate *Tmin*, whilst performing well for *Tmax*, implies that without downscaling the data will be unsuitable (dependent on location) for many CC impact and adaptation studies. Errors will be introduced to estimates of an entity's temperature response, i.e. due to thermal time accumulation, diurnal ranges, biophysical processes etc.. However, the results presented here for mean daily *Tmax* and *Tmin* and their highest and lowest values indicates that the model is capable, after downscaling, of performing well in producing data that represent the natural temperature variability on a daily basis.

The over-estimation of S_o at many locations suggests that the model data without downscaling are unsuitable for use in impacts studies where S_o is a key input. Even where mean values match the seasonal distribution of differences between observed and modelled data, the timing of errors can be important. For example, if the data are used within a crop model, over-estimation of S_o in the spring and summer will result in too high a rate of biomass accumulation (more intercepted radiation). The authors' experience is that data containing compensating errors of the type found in the downscaled S_o estimates can still result in reasonable derived estimations of modelled yield (Rivington *et al.* 2002). The over-estimation of S_o could indicate a weakness in the way the RCM represents cloud cover.

3.5.2 Downscaling Factors method.

Given that both over- and under-estimation of weather variables can occur at the same location, there is a risk of introducing significant errors for applications where estimates, e.g. of soil water deficit, are derived from several weather variables. The use of DF greatly improves the quality of hindcast estimates compared with observed data, hence there will be an associated improvement in estimates derived from the variables. However, DF_{mat} does introduce additional errors in the largest precipitation events. This is due to the DF_{mat} being applied proportionally to the magnitude of the event, hence the largest 3-4 modelled events can become excessively large. Hence care would be needed if the data is used in hydrological modelling of flood risk assessment. The trade-off with the DF_d and DF_{mat} methods is that they do correct well for the vast majority of small to medium sized precipitation events. Also, the temperature DF, whilst improving the representation of means, do not eradicate model biases for extreme low and high temperatures. Practitioners using any form of downscaling technique need to be aware of how remaining or exacerbated biases, such as those above, will manifest themselves when used in CC impacts studies.

Greater confidence can be gained in the future projections of derived estimates (e.g. soil water deficit) after adjustment of the input weather variables by the DF. However, further development potential exists, to relate the DF to the future atmospheric physical properties and role of radiative forcing, i.e. relationship with air temperature and cloud formation. The current assumption that the hindcast dry days bias will persist into the future projections may be misleading, due to changing atmospheric dynamics, hence DF_d may over-correct.

The DF are applied to individual weather variables independently and do not take into account the correlation between variables. The model appears to represent the cross correlation between variables well, and the DF only strongly affect the mean and variance per variable, hence their impact on cross correlation should be minor. The ability of the DF to improve the quality of estimates appears to be spatially and temporally uniform.

3.6 Conclusions.

This research has shown the value of appraising the ability of RCM to replicate the historical climate in order to better evaluate the quality of future projections. The evaluation of the HadRM3 RCM has shown that it produces estimates of the historical climate that will introduce additional uncertainty when used in climate change impact and adaptation studies. The model produces an excess of small precipitation events (< 0.3 mm), whilst giving either accurate or large over- and under-estimations of mean annual total, variable with location. Estimate quality is better for *Tmax* than *Tmin*, which the model tends to over-estimate. Generally the lower values of *Tmax* and higher values of *Tmin* are estimated well. The model systematically over-estimates solar radiation, but does produce good quality estimates at a few sites. The combination of these errors implies that the original estimates are unsuitable for use in detailed climate change impact and adaptation studies, e.g. those concerned with daily time steps like CropSyst. However, the hindcast model estimates are sufficiently similar to observed data in many cases to raise the potential for downscaling.

Where there are significant differences between observed and RCM hindcast data this Chapter has shown that simple, non-statistically based bias correction Downscaling Factors (DF) can be applied that result in a considerably closer match between observed and modelled hindcast data. Improvements in data quality are spatially and temporally uniform. With the assumption that the type and approximate magnitude of errors occurring in the hindcast estimates are repeated in the modelled future climate, then the application of DF means that greater confidence can be placed in RCM projections for particular locations that may be of interest to decision makers. Without the use of a suitable downscaling approach, or until RCM improve further to better represent the historical climate, then site-specific climate impacts and adaptation studies using original RCM data are likely to have significant introduced uncertainty.

Chapter 4: Modelling uncertainty and data quality.

4.1 Abstract.

This Chapter investigates the complexities in using climate model projections within climate change impacts and adaptation studies. It is illustrated by using original and downscaled weather data from Chapter 3 and the uncertainties introduced to CropSyst estimates of crop growth. A cautionary warning on the dangers of making projections of climate change impacts based on uncertain input data is given. Observed, Original hindcast (OH) and bias corrected downscaled hindcast (DsH) data were used within CropSyst to establish the effect of data source on a range of estimates. Crop simulations were then run using HadRM3 data for the A2 medium-high emissions scenario (2070-2100) (OFP), and bias corrected downscaled OFP data (DsFP). The affect on CropSyst estimates were explored in the light of lessons learned from the evaluation of the weather data sources (Chapter 3) and impacts for the past climate.

Though the bias correction improved the match between observed and hindcast data, this did not always translate into better matching CropSyst estimates. At four sites the OH data produced near identical mean yield values as from the observed weather data, a situation of 'right result for the wrong reasons'. This was due to compensating errors in the input weather data and non-linearity in processes represented within CropSyst, making interpretation of results problematical. Overall, downscaling improved the quality of CropSyst estimates. Understanding how introduced uncertainties manifest themselves gives greater confidence in the utility of environmental model estimates produced using downscaled future climate projections. The results indicate implications on how future projections of climate change impacts are interpreted. Fundamentally, considerable care is required in determining the impact weather data sources have on climate change impact and adaptation studies.

4.2 Introduction.

It has been demonstrated in Chapter 3 that the evaluation and downscaling approach improves the quality of future projection data for site-specific application. Evaluation of how uncertainties manifest themselves within environmental models is then required. This helps decision makers understand the various sources of uncertainty in the climate scenarios and how they effect model-based impacts studies so that they have appropriate levels of confidence in the projections and outputs. It is also necessary to consider the types of information required by decision makers, so as to target evaluation efforts accordingly.

This Chapter uses CropSyst to evaluate how estimates of crop yield, phenology and evapotranspiration (ET) varied between observed, original (50×50 km grid cell scale) and downscaled RCM weather data for the past climate (1960-1990). Lessons learned from the effect of data source for the current climate were then used to assess future climate projections more reliably. The aim was to illustrate the consequences on environmental model outputs arising from using either original estimates directly from an RCM or from downscaled estimates. It was not the purpose of this Chapter to make projections of future crop yield, phenology or ET *per se*, as there are substantial crop model calibration, validation and elevated CO_2 response issues (see section 2.8) that are not addressed here. However, the results are informative of possible crop responses, and help to place the magnitude of errors arising from other sources of uncertainty (i.e. CO_2 enrichment) into context. It is argued that the lessons learned from the behaviour of the crop model can be informative to other types of models. Fundamentally, I argue that any impact, adaptation or mitigation study using climate model projection data needs to evaluate whether the data is fit for purpose or not, and then assess the uncertainties that may be introduced and how they manifest themselves. It then becomes possible to develop better informed adaptation and mitigation responses.

CropSyst is a suitable tool to illustrate the effects of weather data quality, as its outputs are a result of the combination of multiple weather variable interactions on non-linear processes. Because of this, relatively small biases in weather data from different sources can manifest themselves in model estimate errors that are not immediately obvious or intuitively explained. Compensating errors may exist, both within a single weather variable's data, i.e. over-estimation on one day, under-estimation on the next, and between variables, i.e. over-estimation of temperature, under-estimation of solar radiation (Rivington *et al.* 2005). These types of compensating errors confuse the interpretation of model estimates and run the risk of getting plausible outputs, but for the wrong reasons. For example, it is possible to produce the same thermal time accumulation rate from two very different temperature data sets. Such errors will affect plant and insect phenological development estimation and relationship with other environmental processes. Therefore we need to understand how the quality and characteristics of climate projection data influence the output from environmental models (how errors manifest themselves) in order to have greater confidence in their utility.

4.3 Materials and Methods.

4.3.1 Weather data sets.

The weather data used is detailed in Chapter 1 and Chapter 3. The five weather data sets were created:

- Observed (Obs).
- The HadRM3 initial realisation original hindcast for 1960-90 (Original Hindcast: OH).
- The OH data downscaled using the method in Chapter 3 (Downscaled hindcast: DsH).
- The HadRM3 estimates for the SRES A2 (medium-high GHG emissions) original future projections for 2070-2100 (Original Future Projection: OFP).

- The OFP data downscaled using the method in Chapter 3 (Downscaled Future projection: DsFP).

4.3.2 Crop simulation.

A generic CropSyst spring barley simulation was calibrated against the Home Grown Cereals Authority (HGCA, http://www.hgca.com/) data set of spring barley trials, so as to achieve national level yield, phenological development rates and harvest dates, and were based on those used by Rivington *et al.* (2006b). The model was parameterised so as to produce estimates with a mean of 7.0 t ha^{-1} grain dry matter from the observed meteorological data. The generic spring barley crop was then simulated at 13 locations in the UK (Fig. 2) such that the only differences between simulations were the input meteorological data. Each year was run separately, with the initialisation values (soil water, soil nitrogen content etc.) being reset on the first day of each year. Hence there was no carry-over effect. Soil texture was set to represent a sandy loam, with water content set such that it was at field capacity on the first day of each year. Management parameters were set so that the crop was not nitrogen limited.

CropSyst does not take into account limitations through weed competition or effect of pests and diseases. Extreme heat stress effect on grain development itself is not represented, but canopy temperature and water stress is considered. The Priestley-Taylor model within CropSyst calculated potential and actual evapotranspiration (PotET and ActET) and a Finite Difference model used for soil water infiltration. Sowing date was always the 15th March and harvest occurred 10 days after the crop reached physiological maturity.

CropSyst was initially run using Obs, OH and DsH weather data, and then the OFP and DsFP. Estimates evaluated were yield, phenological development (beginning of flowering and physiological maturity), potential and actual evapotranspiration and growing season precipitation. Additional CropSyst outputs (e.g. leaf area index, water stress index etc.) were also used for analysis purposes. The use of a spring barley crop restricts the influences of weather data on model estimates to the spring and summer. Hence uncertainties in RCM estimates in autumn and winter and their impact on crop model output are not assessed here.

4.4 Results.

4.4.1 Climate data quality and crop model estimates.

Tables 5-8 provide yield, phenology, crop duration precipitation and PotET and ActET values respectively, derived from the five data sources. Fig. 19 histograms show the frequency distribution of yield per site and data source. Values given as ‘observed’ are not replications of actual observed yields etc., but are crop model outputs derived from observed weather data. Similarly, years referred below for OH or DsH are not actual years but are within the RCM simulated 1960-90 period.

4.4.1.1 Yields.

Two aspects are clear from Table 5: at some sites DsH appears to make the mean yield estimates worse, and at Inverness and Mylnefield OH derived mean yields are considerably below the observed. Across all 13 sites there is a large range in overall response. At all sites the DsH results in over-estimations of yield, ranging between 0.19 to 1.76 t ha^{-1}, but actually improves the closeness of fit with the Obs yields at 7 of the 13 sites.

At Bush, Cawood, Rothamsted and East Malling, the OH derived mean yield estimates match very well those from observed weather data (deviation within 0.02 to 0.09 t ha^{-1}), and are substantially better than those from DsH. However, the frequency distribution of yields is different between Obs and OH (Fig. 19). Using East Malling as an example, the OH yield is within 0.02 t ha^{-1} from the Obs, whereas the DsH yield is over-estimated by 1.05 t ha^{-1}. Given the improvement in match between Obs and DsH weather data, it would be expected that DsH crop model estimates would be more similar to Obs.

Table 5. Differences in yield (t ha-1) between observed weather data sources and original and downscaled Regional Climate Model data for the current (hindcast) and future projections.

	Yield differences (t/ha)								
		Original		Downscaled		Original		Downscaled	
	Obs	hindcast (OH)		hindcast (DsH)		Future (OFP)		Future (DsFP)	
	Yield	Yield	Diff	Yield	Diff	Yield	Diff	Yield	Diff
Aberdeen	7.45	7.99	0.54	8.35	0.90	7.31	-0.14	7.83	0.38
Auchincruive	7.51	7.16	-0.35	7.70	0.19	7.38	-0.13	6.95	-0.55
Bracknell	6.66	7.61	0.95	7.13	0.47	6.15	-0.51	5.86	-0.80
Bush House	7.86	7.84	-0.02	8.38	0.52	6.64	-1.22	7.20	-0.66
Cawood	6.52	6.61	0.09	7.09	0.57	6.23	-0.29	6.50	-0.03
East Malling	6.40	6.38	-0.02	7.45	1.06	5.48	-0.92	6.13	-0.26
Everton	6.48	7.32	0.84	7.23	0.76	6.00	-0.48	5.90	-0.58
Galasheils	7.28	7.82	0.54	8.31	1.03	7.49	0.21	6.99	-0.29
Inverness	6.60	2.60	-4.00	8.35	1.76	3.08	-3.51	7.02	0.42
Mylnefield	7.17	2.49	-4.68	7.70	0.53	5.61	-1.56	6.88	-0.29
Rothamsted	6.97	6.99	0.03	7.49	0.53	5.85	-1.12	6.19	-0.78
Sutton Bonington	6.80	7.64	0.85	7.11	0.32	6.25	-0.55	5.89	-0.91
Wallingford	6.41	7.43	1.01	6.78	0.37	5.92	-0.50	5.51	-0.91
Mean	6.93	6.61	-0.32	7.62	0.69	6.11	-0.82	6.53	-0.40

4.4.1.2 Frequency distribution of yields.

Figure 19 shows the frequency distribution (with a normal distribution fit) of yield estimates from the five data sources. The DsH data results in a skeweness to the right, with the frequency being condensed into the upper classes of yield amount. This reduction in variation is also seen in the OH based estimates at several sites. At Inverness and Mylnefield the OH yields are skewed to the left, reflecting the severe yield under-estimation at these sites. At Inverness the DsH replicates the Obs yield frequency better, but at Mylnefield the DsH results in a concentration of yield frequency around the 8 t ha^{-1} range. In the Scottish sites of Aberdeen, Mylnefield, Bush, Galashiels and Auchincruive DsH shows a clear reduction in yield distribution range and heightened kurtosis.

This is less evident in the locations in central and southern England. At Rothamsted and Wallingford, for example, the DsH was able to reproduce the frequency distribution well. A similar pattern is seen between Obs and OH yield estimates at East Malling, whereas DsH has right skeweness and heightened kurtosis.

4.4.1.3 Phenology.

Across all sites, crop phenological development showed little difference between OH and DsH (Table 6). For beginning of flowering, OH under-estimated by only 2 days for the mean of all sites, and by 1 day by the DsH. At individual sites, the largest OH difference was an over-estimation of 7 days at Auchincruive (bias corrected to DsH = 0). The largest DsH error was an over-estimation of 4 days at Galashiels (here OH was an under-estimation of 4 days). For physiological maturity, the mean for all sites and data sources was within 1 day. OH’s largest error was at Auchincruive (over-estimation by 10 days, bias correct in DsH to 0). DsH produced its largest error at Galashiels, an over-estimation of 6 days, where OH gave an under-estimation of 5 days. These values reflect the generally good performance of the HadRM3 at estimating *Tmax* and *Tmin* for the spring to early summer period (Fig. 8 Ch 3) and that the same thermal time accumulation can be achieved from two different temperature data sets. Importantly, they provide evidence that differences in phenological development are unlikely to contribute much to the differences seen in yields.

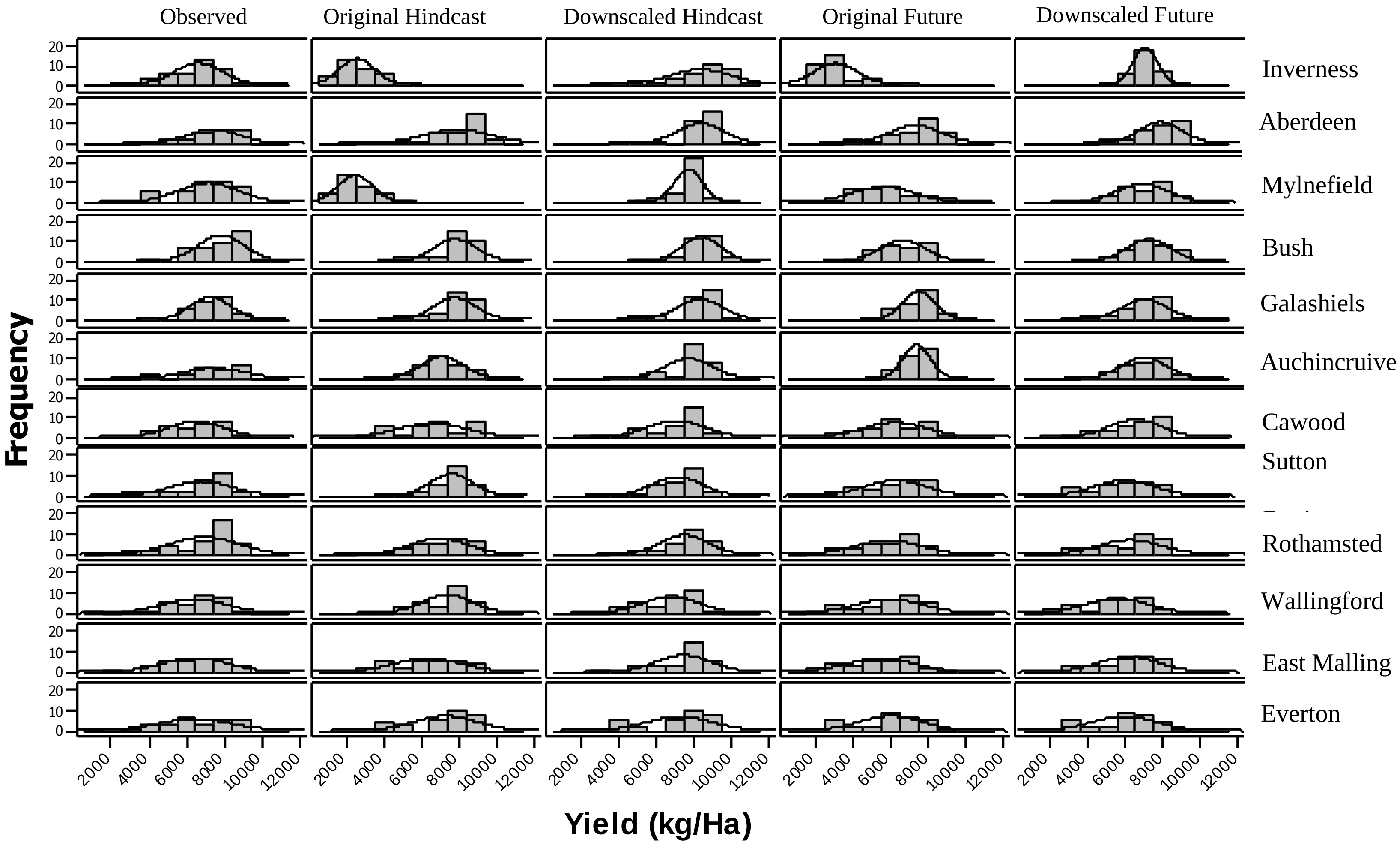


Figure 19. Spring barley yield distribution frequencies from observed, HadRM3 original hindcast, downscaled hindcast, original future projection (A2 scenario) and downscaled future projection data.

Table 6. Phenological growth stages of spring barley from five weather data sources. Obs = Observed, OH = original hindcast, DsH = Downscaled Hindcast, OFP = Original Future Projection, DSFP = Downscaled Future Projection.

	Begin flowering (day of year)					Physiological maturity (day of year)				
	Obs	OH	DsH	OFP	DsFP	Obs	OH	DsH	OFP	DsFP
Aberdeen	175	175	174	155	153	211	213	211	189	188
Auchincruive	166	173	166	154	148	201	210	201	187	181
Bracknell	159	159	160	142	143	192	191	193	171	172
Bush House	173	170	174	151	154	210	205	211	183	187
Cawood	162	165	163	147	146	196	198	198	177	176
East Malling	157	157	158	140	141	189	188	190	168	170
Everton	156	160	158	143	141	189	191	191	171	170
Galasheils	174	170	178	154	154	210	205	216	187	187
Inverness	165	172	166	153	148	201	206	201	185	181
Mylnefield	167	172	166	151	149	203	206	201	182	181
Rothamsted	161	159	163	142	145	194	191	196	170	174
Sutton Bonington	160	163	162	145	144	194	196	195	175	174
Wallingford	159	160	160	142	143	192	192	193	171	172
Mean	164	166	165	148	147	199	199	200	178	178
St Dev	5	4	5	4	4	5	5	5	5	5
Min	154	158	158	138	137	189	190	190	168	167
Max	172	175	175	155	154	207	208	209	186	186

4.4.1.4 Evapotranspiration.

Table 7 and Figure 20 show the mean values for potential and actual ET for each site and data source. At 11 sites, the DsH data improves the match with Obs for PotET, but at only 5 sites for Act ET. This becomes 10 sites for PotET – ActET for the DsH data. Again, at Inverness and Mylnefield, the OH data produces over-estimates of mean Pot ET (217 and 58 mm, respectively) compared to the Obs, whilst ActET is under-estimated (55 and 76 mm, respectively). However, the DsH data does improve the estimates, particularly for Inverness, where the OH PotET – ActET is over-estimated by 272 mm, compared with the DsH's difference of 24 mm. This is due to an over-compensation of ActET (OH under-estimates by 55 mm, DsH over-estimates by 59 mm). At several sites, i.e. Bush, the OH data produce PotET, ActET and PotET – ActET values that are very close to those from Obs.

Table 7. Potential (Pot) and Actual (Act) Evapotranspiration (ET) from five weather data sources. Obs = Observed, OH = original hindcast, DsH = Downscaled Hindcast, OFP = Original Future Projection, DsFP = Downscaled Future Projection. Grey shaded values indicate best data source (lowest difference from observed)

		Evapotranspiration differences (mm) (Estimated - Observed)								
	ET	Obs	OH	Diff	DsH	Diff	OFP	Diff	DsFP	Diff
Aberdeen	Pot	371	390	19	374	2	361	-11	348	-23
	Act	274	289	15	299	24	249	-26	265	-10
	Pot -Act	97	101	4	75	-22	112	15	84	-13
Auchincruive	Pot	377	341	-35	382	6	336	-40	383	6
	Act	277	287	11	289	12	271	-6	252	-24
	Pot -Act	100	54	-46	94	-6	65	-35	131	31
Bracknell	Pot	368	393	25	376	8	384	16	371	3
	Act	255	283	28	265	10	238	-17	225	-30
	Pot -Act	113	110	-3	111	-2	146	33	146	33
Bush	Pot	377	374	-4	385	8	363	-14	366	-11
	Act	291	285	-6	307	16	237	-54	252	-39
	Pot -Act	86	88	2	78	-8	126	40	114	28
Cawood	Pot	357	398	41	360	3	379	22	345	-13
	Act	244	260	16	260	16	229	-15	228	-16
	Pot -Act	114	138	25	100	-14	150	36	117	3
East Malling	Pot	369	412	43	369	0	388	19	352	-17
	Act	244	248	4	269	25	219	-25	230	-14
	Pot -Act	125	163	39	100	-25	169	44	122	-3
Everton	Pot	396	412	16	399	3	397	1	391	-5
	Act	248	279	31	270	22	235	-13	229	-19
	Pot -Act	148	134	-15	129	-19	162	14	162	14
Galashiels	Pot	361	375	14	397	36	350	-11	361	0
	Act	278	286	8	314	36	268	-10	249	-29
	Pot -Act	83	89	6	83	0	83	-1	111	28
Inverness	Pot	329	546	217	412	83	384	55	299	-29
	Act	243	188	-55	302	59	166	-77	236	-7
	Pot -Act	86	358	272	110	24	218	133	63	-22
Mylnefield	Pot	367	425	58	332	-35	388	21	355	-13
	Act	263	187	-76	272	9	213	-50	234	-29
	Pot -Act	104	237	133	60	-43	175	71	120	17
Rothamsted	Pot	367	394	27	372	5	382	15	364	-4
	Act	262	265	3	276	14	229	-33	235	-27
	Pot -Act	105	129	24	96	-9	153	48	129	24
Sutton	Pot	354	380	26	357	3	375	21	356	2
Bonington	Act	250	285	35	262	12	234	-16	219	-32
	Pot -Act	104	95	-9	95	-9	141	37	137	34
Wallingford	Pot	362	388	26	367	5	382	19	365	2
	Act	243	276	32	253	10	230	-13	214	-29
	Pot -Act	119	112	-6	114	-5	151	32	150	31
Mean	Pot	366	402	36	376	10	375	9	358	-8
	Act	259	263	4	280	20	232	-27	236	-23
	Pot -Act	106	139	33	96	-11	142	36	122	16

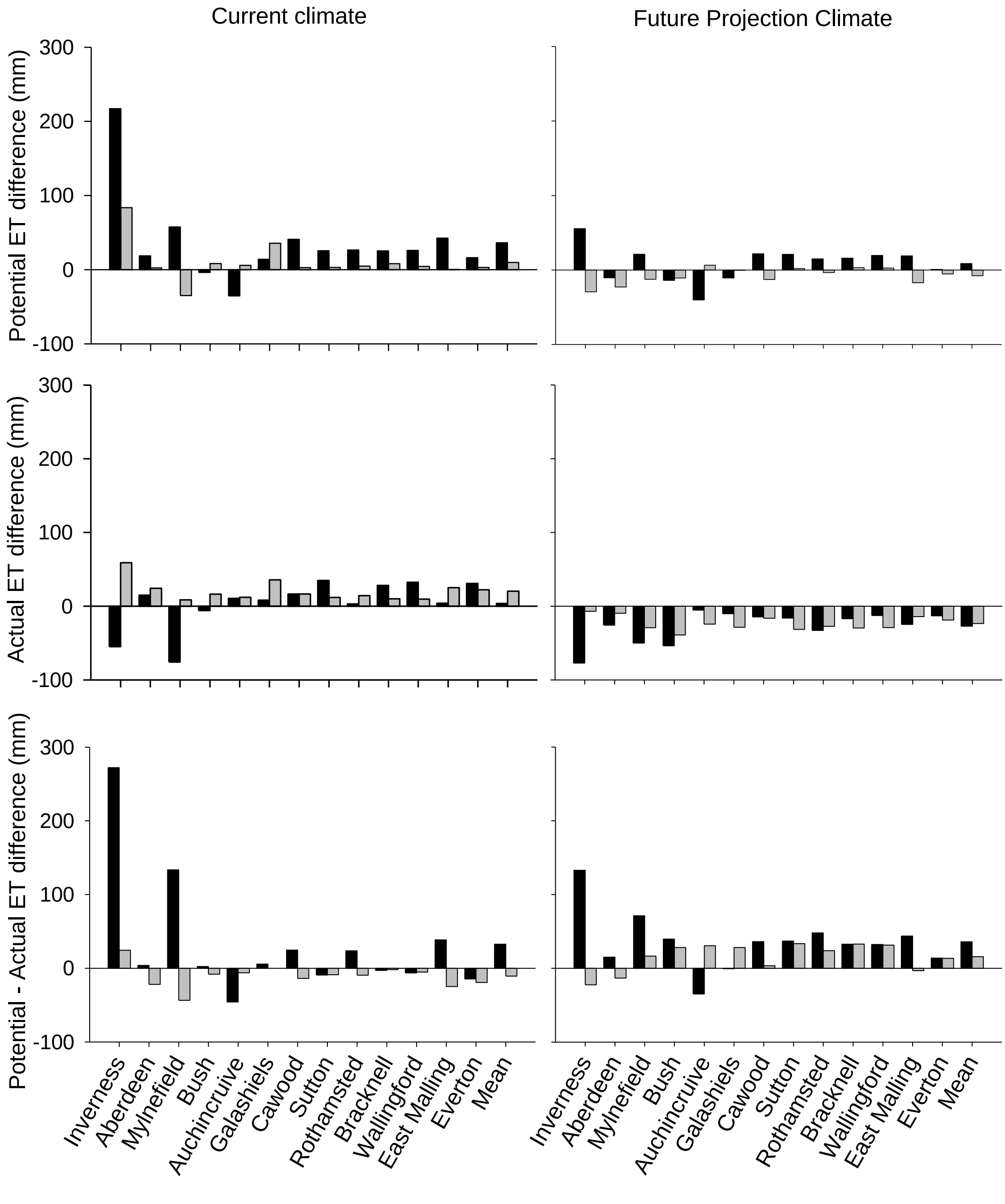


Figure 20. Difference in mean evapotranspiration (ET) during crop growth derived from observed weather data and HadRM3 original hindcast (OH, black bars) and downscaled HadRM3 hindcast (DsH, grey bars) (Estimated – Observed) for the current climate, and difference in ET derived from observed weather data and original HadRM3 data (OFP, black bars) and downscaled HadRM3 data (DsFP, grey bars) for A2 future projected climate.

4.4.1.5 Growing season precipitation.

The OH data gives two sites with large errors of growing season mean precipitation compared with the Obs, at Auchincruive (over-estimation of 292 mm) and Mylnefield (under-estimation of 113 mm) (Table 8). Conversely at East Malling the OH has a difference of only 7 mm. DsH consistently results in an over-estimation, but improves the amount at 6 sites compared with OH. At Aberdeen the DsH makes the mean worse by 70 mm, but at Auchincruive reduces the error to just 24 mm and at Mylnefield it over-corrects to an over-estimation of 50 mm.

Table 8 Growing season (planting to harvest) precipitation (mm) for the five data sources tested: Obs = Observed 1960-90; OH = original HadRM3 hindcast; DsH = Downscaled HadRM3 hindcast; OFP = Original Future projection; DsFP = Downscaled Future Projection.

	Growing season mean precipitation (mm)								
	Obs	OH	diff	DsH	diff	OFP	diff	DsFP	diff
Aberdeen	273	293	20	365	93	232	-40	295	22
Auchincruive	284	575	292	308	24	432	148	240	-44
Bracknell	213	266	53	230	17	189	-24	164	-49
Bush House	319	290	-29	361	42	211	-107	260	-59
Cawood	202	222	21	233	31	180	-21	191	-10
East Malling	192	198	7	239	47	147	-44	176	-15
Everton	193	251	57	234	41	186	-8	176	-18
Galasheils	275	290	15	359	84	335	61	250	-25
Inverness	218	163	-55	290	71	93	-125	216	-2
Mylnefield	240	127	-113	290	50	158	-82	211	-29
Rothamsted	222	233	11	259	37	166	-56	183	-39
Sut'n Bonington	202	290	88	243	42	194	-8	164	-38
Wallingford	185	253	68	210	25	173	-12	144	-41
Mean	232	265		278		207		205	
Total			434		604		-320		-347

4.4.1.6 Analysis of error source.

Closer inspection of CropSyst outputs indicates that for OH, the right mean yield value is being produced, but for the wrong reasons. This is illustrated in Fig. 21 for East Malling for the simulated year 1975, where the OH yield was 6.16 t ha-1 and DsH was 7.54 t ha-1 (which are similar to the mean yields: Obs = 6.40, OH = 6.38 and DsH = 7.45 t ha-1, respectively – see Table 5).

Here conflicting weather variable influences determining the growth of the crop results in different yields. On the one hand the OH S_o data is over-estimated, which would normally give greater biomass accumulation than in the DsH simulation. Conversely, the ActET from OH is lower than from DsH. The DsH *Tmin* is lower than that from OH, whilst each precipitation event magnitude is greater. The day of year for reaching phenological stages also varies: i.e. beginning of flowering is the same, OH = 164, DsH = 164; but peak Leaf Area Index (LAI) differs: OH = 169, DsH = 178, therefore DsH has longer to accumulate leaf biomass; and physiological maturity, OH = 195, DsH = 190. For the crop duration precipitation OH = 207 mm, DsH = 240 mm and OH PotET – ActET = 156 mm, DsH PotET – ActET = 82 mm, hence more water was available to the DsH crop and with a greater ET efficiency. For N uptake in the total above ground biomass, OH = 173 kg N/ha, DsH = 214 kg N/ha, giving a 41 kg N/ha additional uptake.

Mylnefield was a site where OH resulted in a substantial under-estimation of yield. Using the simulated year 1973 as an example (Fig. 22) where OH yield = 2.31 t ha^{-1} and DsH = 8.12 t ha^{-1} (the means were Obs = 7.17, OH = 2.49, DsH = 7.70 t ha^{-1}, Table 5), the OH crop becomes water stressed from day 158, as Pot ET – Act ET differences increase and LAI expansion stops. This can be attributed to OH precipitation being too low. Observed, OH and DsH *Tmax* and *Tmin* are very similar during the growth period, and S_o is greater for OH in the early stages of growth, but very similar for the remaining time. A similar situation is found at Inverness, where the OH gave an under-estimation of 4.00 t ha^{-1}, but the DsH data gave an over-estimation of 1.76 t ha^{-1}.

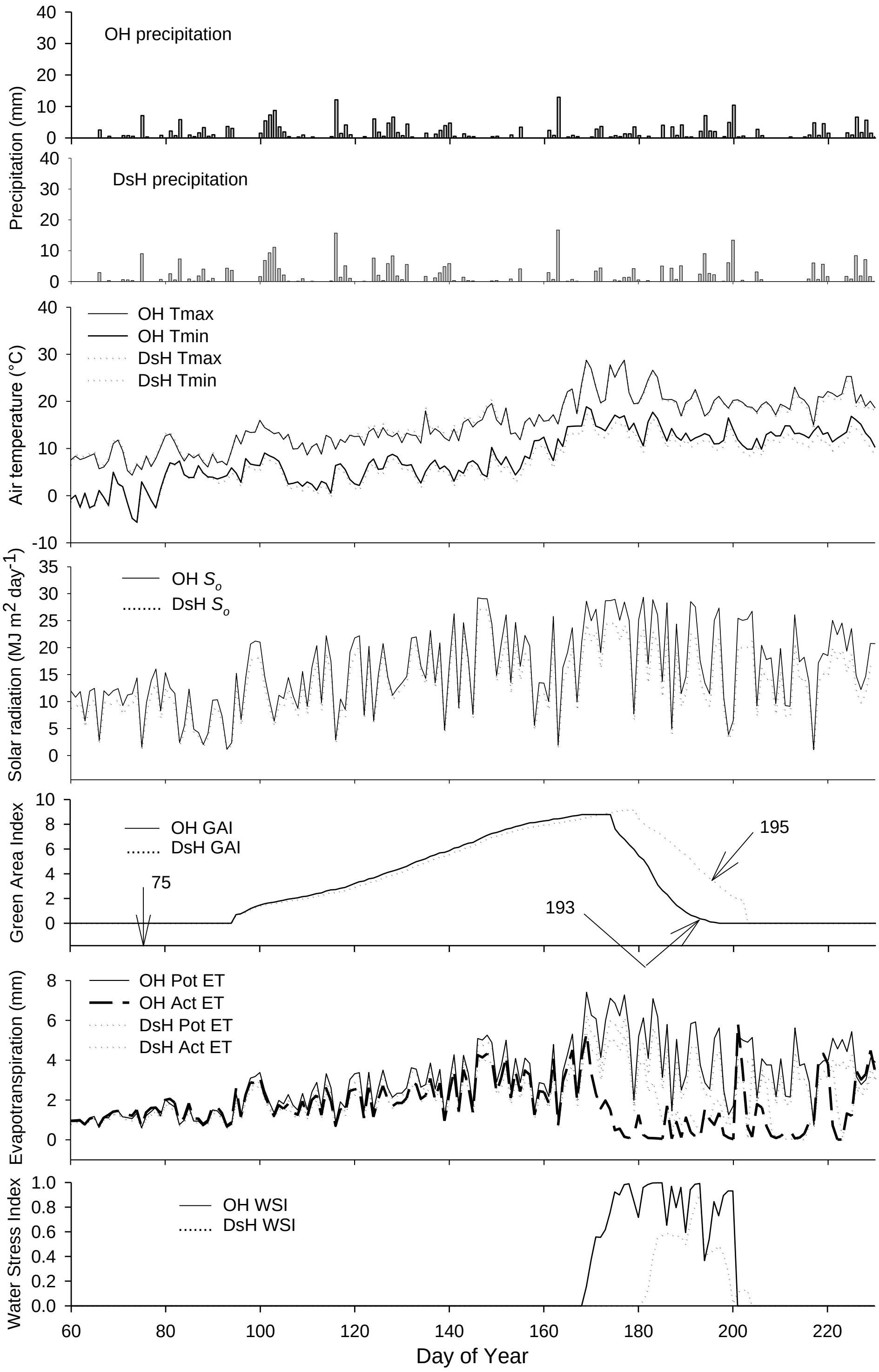


Figure 21. Comparison of HadRM3 original hindcast (OH) and downscaled hindcast (DsH) estimates of precipitation, *Tmax*, *Tmin* and solar radiation (S_o) for a simulated year at East Malling (1975) and their impact on CropSyst outputs: Green Area Index (arrows and numbers show day of sowing and maturity); Potential (Pot) and Actual (Act) Evapotranspiration, and a unitless Water Stress Index. OH yield = 6.16 t/ha, DsH yield = 7.54 t/ha, Observed (1960-97) mean yield = 6.40 t/ha.

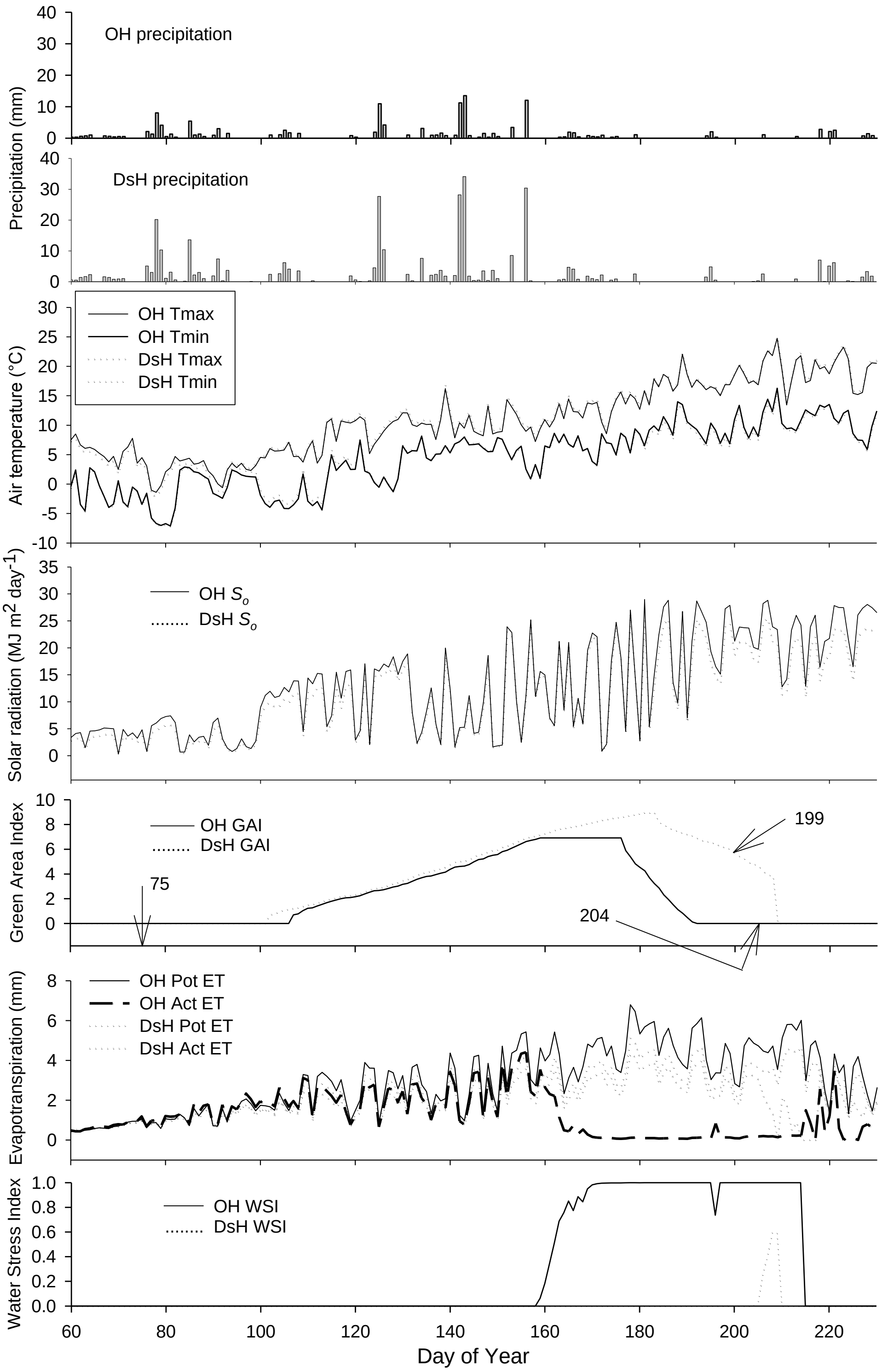


Figure 22. HadRM3 original hindcast (OH) and downscaled hindcast (DsH) estimates of precipitation, *Tmax*, *Tmin* and solar radiation (S_o) for a simulated year at Mylnefield (1973) and their impact on CropSyst outputs: Green Area Index (GAI) (arrows and numbers show day of sowing and maturity); Potential (Pot) and Actual (Act) Evapotranspiration, and a unitless Water Stress Index. OH yield = 2.31 t/ha, DsH yield = 8.12 t/ha, Observed (1961-98) mean yield = 7.17 t/ha.

4.4.2 Future Projections.

The results given here are without CO_2 enrichment, and without re-parameterisation based on potential changes to crop cultivars, hence actual future yields could be different. Projections are also based on one scenario (A2) from one climate model, hence they represent just one possible future outcome. The indications provided by the comparisons of Obs with OH and DsH make evaluation of the future projections problematic. The OFP data gives a reduction in mean yield compared to the 1960-90 Obs derived yields at all sites (except Galashiels), with a mean of 0.82 t ha^{-1} less across all sites, whilst DsFP gives a reduction at 11 of the 13 sites, with a mean of 0.40 t ha^{-1} less (Table 5). However, given that the DsH resulted in over-estimations of yield and OH gave under-estimations, it would seem logical to interpret the OFP yields as being potentially higher, and the DsFP as being lower. This implies that between all sites, the overall mean yield would not be substantially different from the past climate's yield. Phenological development under both OFP and DsH is more rapid, with beginning of flowering and maturity being reached c. 16 and 21 days earlier respectively (Table 6). Uptake in the future of cultivars with slower maturation could increase the length of time for biomass accumulation and hence higher yields (this is not considered here but is currently being researched by the authors).

For PotET, both the OFP and DsFP derived values show greater similarity to values estimated using the Obs weather data than those from the OH and DsH data (Fig. 20). ActET shows a consistent decrease across all sites with both OFP and DsFP (allowing for Inverness and Mylnefield's poor estimates under OH). Given that OH and DsH generally gave an over-estimation of ActET, the results for the future projection ActET could be interpreted as being less of a decrease. The situation of a similar PotET to the current climate, but lower ActET results in a generally positive difference in PotET – ActET at most sites, showing an increase in gap between PotET and ActET.

For the growing season mean precipitation, even though the DsH had given a consistent over-estimation, the DsFP shows an overall decrease in amount, except at Aberdeen. The OFP also shows a decrease, except at Auchincruive (where the OH gave an over-estimation of 292 mm) and Galashiels (where OH was within 15 mm) which shows a potential increase of 61 mm.

The frequency distribution of yields under the DsFP climate conditions, with the exception of Inverness, shows close similarity to that of the Obs, certainly better than that of the DsH (Fig. 19). At Auchincruive, and to a lesser extent Galashiels, the DsFP reduces the kurtosis and evens out the distribution, compared to the OFP. Sites in the south of the UK (i.e. Wallingford) show an increase in the occurrence of low yield events, reflecting an increased potential of water stress related crop growth restrictions.

4.5 Discussion.

The results of running a simple spring barley simulation within a crop model using observed weather data and original and downscaled RCM data, has shown that great care is required in interpreting model outputs. Based on these results, it is possible to see how misleading conclusions could be drawn from research where original climate model estimates are used in modelling studies of future CC impacts. In a hypothetical situation, results derived using observed and original HadRM3 hindcast data and A2 future projections, could have been presented based on the ability of the hindcast data to reproduce mean yields very well for the current climate at some sites. A false indication would then have been interpreted for future yields. Therefore, the assumption that the ability for a modelled weather data source to reproduce outputs from an environmental model with similar properties as those derived from observed weather data may not be safe. Here it is shown that it is possible to get the 'right result' (i.e. mean crop yield) from the original RCM data, when it is known that there are differences between the original modelled and observed weather data.

The downscaling process does improve the goodness of fit between observed and modelled weather data, but it also results in an over-estimation of yields, though overall it is better than the original RCM data. The bias correction method aims to minimise the difference in the means for each variable. In doing so, some daily data values are actually made worse. An example of this is seen in the largest precipitation events, where the DF increases the magnitude proportionally, leading to some large over-estimations for the 4-6 largest events. This implies that the bias correction method in its current form as used here may not be suitable for studies concerned with extreme precipitation events. Also, where the RCM produces seasonal precipitation errors (i.e. over-estimating in the spring, under-estimating in the summer, autumn and winter with an overall mean annual total under-estimation), the bias correction method used here will correct for the mean annual total, giving an increased spring error. The bias correction method adjusts individual variables, not the correlation between them. The yield results for Mylnefield indicate the need for all weather variables to be correct. Here the OH weather data was generally close to the Obs, apart from precipitation and solar radiation. The bias correction of the OH data gave better results related to these variables, but the combined effect across all variables was that mean yield was over-estimated by 0.53 t ha^{-1} (compared to OH under-estimate of 4.68 t ha^{-1} , see Table 5).

Another issue is that the impacts of weather data source assessed here was limited to the spring and summer growing season. For *Tmax* and *Tmin*, the HadRM3 produces estimates close to the means of observed data for this period, but generally over-estimates S_o. The impact of data source on environmental models making simulations covering an entire year, or multiples of years with carry-over effects between years, will be different again, as the magnitude of differences between modelled and observed weather data changes. As such, many important whole year processes were not evaluated, including issues of extreme cold in winter, crop vernalisation requirements, autumn soil water recharge etc.. Given that a downscaling method will correct over the entire year, it appears reasonable to extrapolate that the output from environmental models running over long periods will improve with downscaling, but with the same caveats as above.

Whilst the data sources tested had little effect on crop phenology, ET was different. This is a key subject within both crop and hydrological modelling, the indications being that very different ET estimates are produced depending on data source. This will have a serious impact on strategic planning for water management. Though not evaluated in this study, it is logical to assume that other model estimates (nitrogen use, soil water balance, carbon sequestration etc.) will also differ between data sources.

Based on these results, I argue that the types of errors manifesting themselves due to data source in crop model estimates will also occur in other types of environmental models (ecological, hydrological etc..). The lessons learned from the behaviour of the crop model can be informative to these other models. Though not tested here, it would seem logical that other types of downscaling (i.e. statistical or weather generators) and other bias correction methods, would also have a similar form of impact. Quantification of the magnitude of errors introduced by weather data source helps place the uncertainties within context of other error sources. For example, elevated CO_2 levels can lead to increased leaf level photosynthesis and reduced transpiration (i.e. Leakey *et al.* 2009), hence giving greater biomass production. For a winter barley Free Air Carbon-dioxide Experiment (FACE), one reported value is 14.4 % increase in biomass (Weigel *et al.* 2006), another is 20 % for spring barley (Saebo and Mortensen 1996). Using the Obs mean yield value of 6.93, increasing by 14.4% (0.997 t ha^{-1}) gives 7.29 t ha^{-1}, and by 20 % (1.386 t ha^{-1}) gives 8.32 t ha^{-1}. This example difference of 0.389 t ha^{-1} reflecting the uncertainties due to CO_2 enrichment are comparable with the magnitudes of errors associated with climate data source seen here. Hence future projections using models to estimate plant responses need to consider not just the physiological response due to elevated CO_2, but also the uncertainty in the quality of input weather data.

The frequency distribution of yields varies between data source. This is important as, though means are useful indicators, in terms of land manager responses and decision making, it is the variability and risks that are more informative. Based on the DsH results, the bias correction method appears to condense yield estimates into a narrower range around the mean (heightened kurtosis), though this does not seem so obvious in the DsFP results (Fig. 19). Therefore interpretations of the distribution of estimates such as yield need to consider how the data source impacts on the frequency distribution and how the interpretations can be communicated to a range of stakeholders for decision making purposes.

4.6 Conclusions.

The utility of future projections of climate change impacts from environmental models is greatly influenced by the quality of data from climate models used to run them. Potentially misleading results are gained when original data from a single climate model are used. The results shown here indicate that care is needed in evaluating the role that input climate change projection data have on the outputs from environmental models. The use of downscaling to correct for differences between the scale of the climate model and that of an environmental model will increase confidence in the quality of its outputs and hence its utility in climate change impacts, mitigation and adaptation studies. However, it must be recognised that the downscaling method itself may also introduce uncertainty to environmental model estimates. This and the preceding Chapter has demonstrated the value gained by conducting an assessment of the ability of a climate model to represent the past climate, and a subsequent evaluation of the impact the data source has on the outputs from a model representing environmental processes. By gaining an understanding of how uncertainties are introduced to models and how they manifest themselves, it becomes possible to make more reliable interpretations of environmental model based future projections. Without such a form of assessment and evaluation, misleading conclusions could be drawn.

Care is needed to ensure that the downscaling method itself used does not alter the outputs from the environmental models, as seen where the frequency distribution of yields was altered by the bias correction method. In this respect it is useful to identify *a priori* what the objectives are for downscaling and how model outputs are to be used. These can be posed as questions such as: what the downscaling must achieve (i.e. maintenance of correlations between variables, ability to represent extremes etc..); what outputs need to be evaluated, and how to perform the evaluation (means may not be appropriate); and what factors are vital for decision making (generalised versus detailed, variability, extremes, risk)? The use of multiple scenarios, probabilistic scenarios or climate model ensemble estimates may on one hand partially alleviate the above issues, but on the other compound the issues of evaluation given the increased amount of data to analyse. Sensitivity analysis would provide more detailed information on the variability of model outputs depending on data quality, but this tends to be resource demanding, hence there is a need for simple, easy to implement methods to evaluate the impacts that data source has.

Fundamentally, this work has illustrated that in order to make more reliable projections of the impacts of climate change and how we might be able to adapt, we need to better understand how the quality of projection weather data used may introduce uncertainties and how these will manifest themselves in environmental model outputs. This Chapter should therefore be taken as a warning against placing too much reliance on the output from environmental models that use original climate model estimates and when evaluation of the effect of data source has not been conducted. The findings shown here should be used as a guide for interpretation of the results detailed in Chapter 6.

Chapter 5: Agro-meteorological metrics.

5.1 Abstract.

Agro-meteorological metrics (Ag-Metrics) are important indicators of environmental conditions on which land management decisions are made. Metrics derived from an estimated future climate provide an opportunity to characterise the impacts of climate change on a wide range of land use practices. Such indications are vital for determining how changes in the biophysical environment can lead to adaptations to achieve financial viability, food security and environmental sustainability. They also provide valuable links between probably management adaptation responses and capacity for achieving mitigation requirements for greenhouse gas emissions. This Chapter describes the estimation of agro-meteorological metrics derived from observed and downscaled Regional Climate Model projection data (Chapter 4) for 12 sites in Scotland. Results show that projected changes to seasonal rainfall distribution, the growing season, soil moisture and accessibility will be substantially different from the present climate. Fundamentally, the metrics indicate a significant shift in land management requirements and potential for substantial changes in land use.

5.2 Introduction.

The objective for this Chapter was to utilise a range of agro-meteorological metrics (Ag-metrics) that encapsulated the main weather and soil related aspects determining land use choices and management at specific locations to indicate change between current and future climates. By estimating Ag-Metrics using observed and downscaled future projection data, analyses could be made as to the magnitude and direction of changes, from which interpretation could be made as indications of the consequences of impacts and help to define the scope for adaptation options. Further details on agro-meteorological metrics is given in Chapters 1 and 2.

5.3 Materials and Methods.

5.3.1 Data sources.

Observed data from the 12 sites in Scotland were used (Fig. 2, Ch 1). The target time period for data use was 1960 to 1990. The future projection data from HadRM3 were downscaled according to the methods detailed in Chapter 4. The Ag-Metrics and a simple soil water balance model (see below) were implemented within the Gensym G2 software development environment within the IMF, which links to the Oracle database via a proprietary software bridge. Ag-Metrics were estimated using observed and downscaled HadRM3 future projection data for each year of available weather data from each of the 12 sites. From this yearly data the mean, 10^{th} and 90^{th} percentiles, and standard deviation were estimated for a selection of Ag-metrics. The mean monthly precipitation was estimated and plotted to illustrate the temporal change in annual rainfall distribution (Fig. 23) and the increase in mean daily temperature estimated (Table 10) as climate summaries.

5.3.2 Agro-meteorological metrics.

For the purposes of this Chapter, Ag-Metrics are defined as values that describe a property, either of the climate itself, or an entity or process that is affected by it. The number and type of elements for each Ag-Met vary with the property being assessed, and can be used as benchmarks for comparisons both within a single site (between Ag-Metrics) and between sites (for the same Ag-Met). Ag-Metrics can be either *quantitative* in that they can be further simplified into categories for presentation (i.e. trends) or *qualified* (i.e. good, bad, neutral).

Table 9. Agro-meteorological metrics and definition used. SMD = soil moisture deficit, P = precipitation, FC = field capacity, SM = soil moisture, PWP = permanent wilting point, ADS = air dried soil, T_{avg} = mean temperature. After Matthews *et al.* 2008a.

Type	Indicator	Metric	S/M	Units
Date	*Start Growing Season*	day when 5 consecutive days T_{avg} > 5.6 °C (from Jan 1st)	S	day of year
	Start of Field Operations	day when $\sum T_{avg}$ from Jan 1st > 200°C (T_{sum}200)	M	
	End of Field Capacity	day when Soil Moisture Deficit (SMD) > 5 mm (from Jan 1st)	S	
	Last Air Frost (Spring)	day when *Tmin* < 0.0 °C (from Jan 1st)	M	
	Last Grass Frost (Spring)	day when *Tmin* < 5.0 °C (from Jan 1st)	S	
	Date of Maximum SMD	day when SMD at maximum		
	Wettest Week	mid week date when maximum 7 day value of P occurs		
	First Grass Frost	day when *Tmin* < 5.0 °C (from July 1st)	S	
	First Air Frost	day when *Tmin* < 0.0 °C (from July 1st)		
	Return to Field Capacity	day when SMD < 5 mm (after date of max SMD)	M S	
	End Growing Season	day when 5 consecutive days T_{avg} < 5.6 °C (from July 1st)		
Count	Air Frost	days when *Tmin* < 0.0 °C	S	days
	Grass Frost	days when *Tmin* < 5.0 °C		
	Growing Season Range	days between Start Growing Season and End Growing Season		
	Growing Season Length	days when T_{avg} > 5.6 °C between Start and End of Growing Season	M	
	Access Period Range	Return to FC– End of FC	S	
	Access Period Length	days when soil moisture < field capacity		
	Dry	days when P < 0.2 mm		
	Wet	days when P > 0.2 mm		
	Plant Heat Stress	days when *Tmax* > 25.0 °C		
	Dry Soil Days	days when soil moisture < permanent wilting point	M	
	Very Dry Soil	days when soil moisture < air dried soil		
Deg Days	Accumulated Frost	sum of day degrees where *Tmin*< 0.0 °C	S	day deg
	Growing Degree Days	$\sum T_{avg}$ > 5.6 °C		
	Heating Degree Days	sum of 15.5 °C - T_{avg} where T_{avg} < 15.5 deg °C		
Water	*Excess Winter Rainfall*	sum of P > soil saturated capacity (runoff and drainage)	S	mm
	Wettest Week - Amount	maximum amount of P (7 consecutive days)	M	
	Minimum soil water	Max SMD		
Waves	*Heat Wave*	maximum count of consecutive days when *Tmax* >Avg *Tmax* (baseline year) + 3.0 °C (minimum 6 days)	S	days
	Cold Spell	maximum count of consecutive days when *Tmin* < Avg *Tmin* (baseline year) - 3.0 °C (minimum 6 days)		
	Dry Spell	max consecutive count P < 0.2 mm		
	Wet Spell	max consecutive count P > 0.2 mm		
Indices	P intensity	$\sum$P > 0.2mm /Count days P > 0.2mm		index
	P seasonality	S = winter P – summer P / total P[6]		
	P heterogeneity	Modified Fournier index		

[6] S < -0.13 (wetter winters); -0.13 < S < 0.13 (uniform) and S > 0.13 (wetter summers)

The Ag-Metrics implemented in the framework are grouped by type and set out in Table 9. The four indicator types are:

- *Date*: when the first or last incidence of a phenomenon occurs.
- *Count*: the number of days on which a criterion is met.
- The *accumulation* of a variable above or below a threshold value.
- *Indices*, where an index value is calculated and compared against a standard.

These Ag-Metrics were chosen as they provide a sufficient range of indicator values determined by the weather that were considered important for land managers. They are not restricted in their application to particular locations, and have an open-ended structure for re-definition, customisation and development. Where the Ag-Metrics can be customised for particular circumstances or activities they are italicised in Table 9, which also notes if it is derived from one or more variables. The intention was not to test new or innovative Ag-Metrics, rather they were drawn from older agro-climatic sources (Francis 1981, Walsh and Lawler 1981, FAO / UNEP 1977) and a more recent source with a climate change focus (Barnett *et al.* 2006). Other Ag-Metrics are drawn from parameter thresholds from crop models, i.e. *heat stress* from the CropSyst cropping systems model (Stöckle *et al.*, 2003).

Matthews *et al.* (2008a) highlighted the preference from stakeholders for Ag-Metrics reflecting the changes in when phenomena occur (*Dates*) and the number of days when a criterion is met (*Counts*). Based on this, empirical cumulative distribution function (CDF) plots were produced for *Dates* at the wet west coast site of Auchincruive (Fig. 24) and the drier east coast site of Aberdeen (Fig. 25) and probability plots for *Counts* (Fig. 26) at both these sites. Polar plots were made of individual Ag-Metrics at multiple sites (Fig. 27), and also of multiple Ag-Metrics at individual sites (Figs. 29 and 30).

5.3.2.1 Soil water balance model.

The soil moisture metrics are derived using a simple soil moisture balance model, (See Matthews *et al.* (2008a) (with further details at LADSS:

http://www.macaulay.ac.uk/LADSS/soil_water_budget.html). This model is based conceptually on that used to derive the agro-meteorological statistics in Francis (1981) which in turn is based on early models by Smith (Ministry of Agriculture Fisheries and Food 1967, Ministry of Agriculture Fisheries and Food 1971). While these simple models have been superseded by models with more sophisticated representations of soils, e.g. NIRAMS (Dunn *et al.* 2004) or the interaction of climate and soils e.g. MOSES (Cox *et al.* 1999) they have the advantage of having relatively modest data requirements, i.e. either via the archives supplemented by local (MLURI 1990), regional (Wosten *et al.* 1999) or stakeholder provided site-specific soils data. The Smith model was updated by Matthews *et al.* (2008a), particularly in relation to the estimation of soil parameters and the calculation of surface runoff.

The SWB model works on a daily time step as follows. First the daily water balance (between precipitation (P) and evapotranspiration (ET)) is calculated. ET is calculated using the Priestly-Taylor equation (Priestley and Taylor 1972). Any P remaining either enters the soil (if below saturation point (SP)) or is lost to the system as surface runoff (SR). Any water in excess of field capacity (FC) and below SP is assumed to drain in three days unless it is used to replace any existing or subsequent deficit below FC (there are thus three surface-water pools used in order of oldest first). Any requirement for ET that has not been met by precipitation is taken from the soil water profile. Between FC and permanent wilting point (PWP) the effective rate of ET is assumed to be 100% for the first layer, 50% for the second and 25% for the third. The ratio of the size of these layers is assumed to be 2:1:1. Below PWP any further ET demand is met at 25% until the soil becomes air-dried (AD).

The principle source of uncertainty in the estimation of actual soil moisture balances is the parameterisation of the soil (Francis 1981). In this regard the framework makes available the most significant parameters that affect the soil moisture balance (depth, texture and organic matter content), and derives either directly or through the use of specialised pedotransfer software such as SOILPAR (http://www.sipeaa.it/ASP/ASP2/SOILPAR.asp) the key parameter values (SP, FC, PWP and AD) as mm of water per m of soil depth. For each site, specific soil types and depths were used based on soil map unit descriptions (MLURI 1990) and an organic matter content of 8%. A limitation of this SWB model is that it does not take into account the effect of elevated CO_2 on plant transpiration rates (within the ET calculations from the Priestly-Taylor model). Higher CO_2 concentration may reduce transpiration, but I considered this to be not such an issue in the relatively wet Scottish climate. Also, there is an associated less certain effect on leaf area index response. The effect of elevated CO_2 is however an important consideration, particularly in drier locations, but one that may better be investigated through more detailed impacts modelling studies. Awareness of the issues of elevated CO_2 should be factored into the interpretation of the SWB estimates.

To illustrate output from the SWB model, the driest and wettest years were identified from the current and future projection data sets (Figs. 31 and 32, respectively). The driest was defined as the year when the soil was drier than the permanent wilting point (PWP) for the longest time, whilst the wettest year was the year with the lowest maximum SMD. A ten year continuous plot was made for the observed (1980-90) and future (2080-90) periods to illustrate the change in frequency of phenomena (Fig. 33).

5.4 Results.

5.4.1 Climate summaries.

5.4.1.1 Average temperature.

Mean daily temperatures were seen to increase by between 1.2°C (at Prabost on the west coast) and 3.4°C (at Aviemore). All sites showed an increase with the spatial pattern reflecting that seen in Hulme *et al.* (2002) of the greatest warming occurring in the east of Scotland. Table 10 gives the increase at a range of sites in Scotland, with a 2.8°C mean increase. The analysis conducted for the climate summaries however did not examine the change in variability of average temperature, as the purpose of these summaries was to give an overview of the magnitude and of the direction of change.

Table 10. Increase in mean daily temperature at selected sites in Scotland.

Site	Temperature change (°C)
Prabost	↑ 1.2
Lairg	↑ 2.6
Aviemore	↑ 3.4
Aberdeen	↑ 2.8
Mylnefield	↑ 3.1
Galashiels	↑ 3.0
Carnwath	↑ 2.8
Eskdalemuir	↑ 3.0
Dumfries	↑ 3.3
Auchencruive	↑ 2.8
Dunstaffnage	↑ 2.9

5.4.1.2 Seasonal rainfall distribution.

Figure 23 shows the mean monthly rainfall distributions for 7 examples sites. Eastern sites show projections of having wetter springs and drier summers (i.e. Aberdeen, Mylnefield and Galashiels), whilst west coast sites show wetter winters and summers similar to the present (i.e. Dunstaffnage and Prabost). These are consistent with other spatial studies (i.e. Hulme *et al.* 2002, Brown *et al.* 2008) and help to interpret the results for Ag-Metrics that use precipitation.

5.4.2 Agro-meteorological metrics: current and future.

The Ag-Metrics are presented in a range of formats to illustrate spatial variation between sites for individual metrics, temporal variation of single metrics at two single sites, and multiple metrics at single sites. Single-site with multiple Ag-Metrics gives a detailed picture on the impacts of a future climate on a range of conditions at a single site and how these may interact with one another. Multiple-sites with a single Ag-Metric allows the regional differences to be observed. Tables 11,12 and 13 give the values of 10th percentile, mean and 90th percentile for all Ag-Metrics at all sites. Further details of Ag-Metrics not described here are available from the LADSS website: (http://www.macaulay.ac.uk/LADSS/comm_cc_consequences.html).

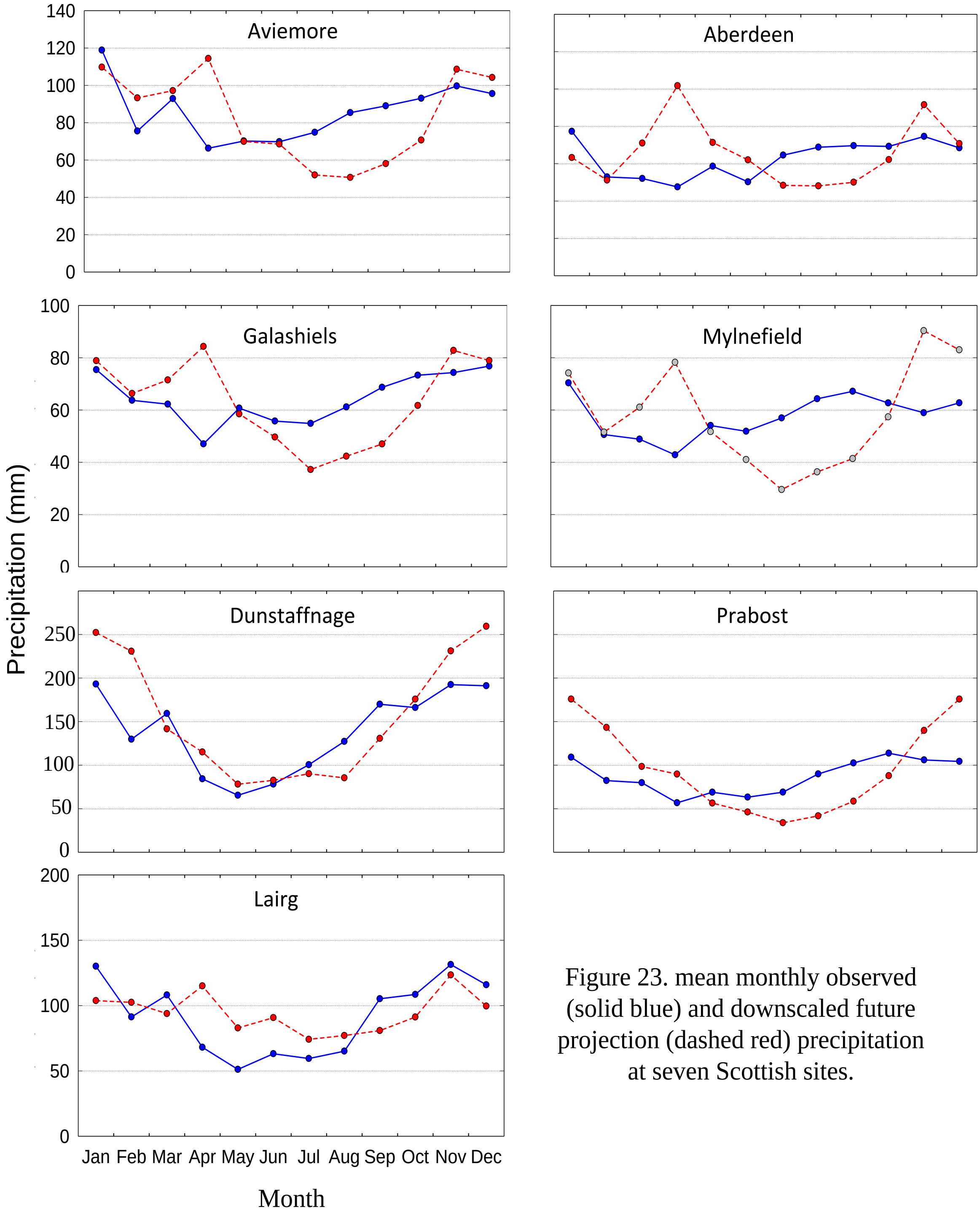


Figure 23. mean monthly observed (solid blue) and downscaled future projection (dashed red) precipitation at seven Scottish sites.

Table 11. Agro-meteorological metric 10th percentile, mean and 90th percentile values derived from observed weather data and downscaled future projection data at Inverness, Aviemore, Aberdeen and Mylnefileld.

Type	Metric name	Units	Inverness								Aviemore								Aberdeen								Mylnefield							
			10th		Mean		90th		SD		10th		Mean		90th		SD		10th		Mean		90th		SD		10th		Mean		90th		SD	
			Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut
Date	Growing Season Start	Day of year	10	1	39	20	75	48	28	20	63	7	93	46	124	74	27	25	17	1	70	26	112	61	15	24	11	1	58	25	101	62	33	24
	TSum200		37	29	55	37	73	47	15	8	56	42	82	53	109	68	20	10	43	32	59	39	77	48	14	7	43	33	60	39	76	51	15	7
	End of Field Capacity		74	74	94	90	107	108	15	16	81	79	102	98	120	112	15	15	78	70	92	89	107	109	13	17	71	69	87	86	100	108	11	14
	Last Air Frost (Spring)		85	55	104	74	122	105	19	20	134	76	150	107	172	132	15	21	102	48	117	76	137	100	15	21	90	53	114	73	154	100	136	20
	Last Grass Frost (Spring)		141	117	155	135	172	152	12	17	173	141	178	158	181	177	3	13	151	115	165	134	180	158	11	16	146	110	161	130	176	142	12	13
	Date of Maximum SMD		169	207	216	248	257	279	37	38	158	201	196	228	240	268	35	31	171	209	219	239	257	269	32	33	195	224	231	250	264	274	29	27
	Wettest Week		33	62	223	201	342	335	104	119	8	72	142	195	312	331	121	111	30	91	215	211	324	327	105	101	50	62	216	208	351	350	107	126
	1st Grass Frost (Autumn)		230	256	252	286	277	310	22	23	184	218	193	248	204	279	11	27	191	280	229	297	264	310	29	16	187	273	226	292	267	308	30	14
	1st Air Frost (Autumn)		286	320	307	333	322	347	17	11	208	297	247	317	274	341	27	18	285	317	299	339	315	359	13	17	277	313	300	332	325	352	18	15
	Return to Field Capacity		268	301	297	333	337	370	30	28	245	256	267	286	297	308	19	20	261	271	285	302	313	339	22	25	274	296	297	317	323	334	22	19
	Growing Season End		316	342	338	354	363	365	18	11	295	319	316	344	350	362	21	18	309	329	332	349	355	365	19	13	311	334	335	352	360	365	19	11
Count	Air Frost	Days	29	9	51	19	76	28	18	8	91	30	114	43	136	56	21	10	41	3	58	11	75	19	14	6	41	12	57	20	79	28	16	8
	Grass Frost		158	90	173	103	187	114	12	10	223	141	238	157	249	171	12	12	165	107	188	121	205	138	14	13	163	98	183	108	202	123	14	12
	Growing Season Range		251	297	301	335	346	362	37	24	187	260	224	299	266	348	29	35	217	290	263	324	333	356	43	27	230	283	277	327	319	359	35	27
	Growing Season Length		242	300	261	315	284	331	18	12	194	260	209	279	229	296	13	14	226	290	244	306	266	320	16	13	232	296	250	312	269	326	15	13
	Access Period Range		173	204	202	241	242	285	32	31	141	156	164	187	191	222	23	26	164	178	192	212	232	247	27	29	182	201	209	230	242	252	22	23
	Access Period Length		118	175	170	219	213	256	43	32	71	128	112	156	162	192	33	27	123	132	164	177	218	218	39	36	140	171	187	206	236	231	34	25
	Dry		162	205	183	219	203	236	18	13	122	144	135	159	154	173	15	13	161	195	182	211	203	225	18	15	170	200	187	216	205	229	14	12
	Wet		163	129	182	146	203	160	17	13	212	192	230	207	243	221	15	13	162	141	184	155	205	170	18	15	160	136	178	150	195	165	14	12
	Plant Heat Stress		0	9	2	18	6	33	2	10	0	8	4	19	11	36	5	11	0	2	1	9	1	21	1	8	0	9	2	19	4	33	2	11
	Dry Soil		0	0	0	0	0	0	0	0	0	0	3	15	15	43	7	18	0	0	1	1	5	5	2	2	0	0	4	16	16	47	8	19
	Very dry soil		0	0	0	0	0	0	0	0	0	0	0	4	0	15	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Accumulated	Frost	Degree days	-189	-54	-111	-30	-40	-8	59	16	-211	-46	-383	-87	-555	-134	143	31	-62	-5	-125	-13	-183	-26	51	9	-60	-11	-127	-30	-188	-58	57	17
	Growing Day Degrees		1324	2102	1457	2300	1595	2526	103	170	889	1685	1029	1875	1181	2114	127	166	1112	1817	1249	2013	1391	2214	104	154	1257	2099	1404	2285	1531	2504	112	162
	Heating Day Degrees		2336	1542	2524	1702	2735	1863	158	118	2952	1992	3257	2158	3526	2327	222	136	2551	1769	2756	1890	2947	2028	160	116	2412	1590	2612	1730	2805	1893	160	107
	Excess Winter Rainfall	mm	210	135	302	253	417	363	105	93	573	456	679	624	872	753	141	118	237	238	380	415	529	573	118	120	210	241	337	343	459	441	108	87
	Wettest Week Amount		43	54	63	82	88	117	21	32	63	71	96	100	132	132	29	35	54	62	74	91	108	135	23	31	46	55	71	78	104	109	22	25
	Max Soil Moisture Deficit		43	90	81	107	111	127	27	19	26	47	44	61	67	68	14	9	49	60	73	79	97	103	18	17	62	84	84	100	105	123	18	16
	Heatwave	Days	3	5	5	8	8	11	2	3	4	5	8	8	12	13	3	4	3	2	5	5	8	7	2	2	2	3	5	6	7	8	2	2
	Dry Spell		11	11	16	18	21	29	4	7	8	10	12	13	16	19	3	4	10	10	14	15	20	24	3	5	11	12	16	18	21	23	4	4
	Cold Spell		3	4	6	6	10	8	3	2	3	4	7	6	10	8	3	2	3	2	6	4	9	5	3	1	3	3	6	6	8	10	2	3
	Wet Spell		10	7	13	9	16	13	4	3	14	11	19	16	24	23	6	5	8	7	12	11	15	16	4	4	9	7	11	10	14	14	2	3
Indices	Precipitation Intensity		4.10	5.10	4.71	6.19	5.30	7.10	0.54	0.85	5.40	5.30	5.96	6.15	6.70	7.00	0.60	0.63	4.96	5.60	5.61	6.85	6.32	7.80	0.57	0.92	4.56	5.60	5.40	6.48	6.04	7.30	0.64	0.67
	Rainfall Seasonality		-0.12	-0.36	0.05	-0.18	0.23	0.05	0.14	0.18	-0.22	-0.42	-0.06	-0.26	0.17	-0.09	0.17	0.13	-0.15	-0.36	0.01	-0.14	0.15	0.15	0.14	0.18	-0.24	-0.41	0.03	-0.25	0.17	0.00	0.16	0.17
	Rainfall Heterogeneity		690	690	854	879	1088	1144	178	240	1071	1057	1314	1286	1627	1636	262	224	757	886	961	1082	1235	1405	198	243	694	737	891	995	1087	1216	181	232

Table 12. Agro-meteorological metric 10th percentile, mean and 90th percentile values derived from observed weather data and downscaled future projection data at Bush, Galashiels, Eskdalemuir and Dumfries.

Type	Metric name	Units	Bush								Galashiels								Eskdalemuir								Dumfries							
			10th		Mean		90th		SD		10th		Mean		90th		SD		10th		Mean		90th		SD		10th		Mean		90th		SD	
			Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut
Date	Growing Season Start	Day of year	27	3	67	30	109	66	33	27	13	3	63	29	108	66	37	26	65	6	96	46	118	79	19	28	4	1	41	16	84	45	30	17
	TSum200		46	36	65	43	84	56	16	9	46	36	68	44	91	59	17	10	53	40	74	49	100	64	19	10	39	29	57	36	80	49	16	8
	End of Field Capacity		81	79	96	94	114	114	14	15	84	78	97	93	107	113	12	16	85	80	105	98	129	122	17	19	66	74	88	90	106	109	15	15
	Last Air Frost (Spring)		104	60	127	87	147	111	15	20	111	72	126	94	144	113	13	16	139	77	152	103	170	122	14	16	99	60	120	80	138	103	15	20
	Last Grass Frost (Spring)		160	126	171	141	181	155	9	14	158	136	169	147	180	162	10	14	170	147	177	159	182	177	5	12	149	121	165	136	179	146	11	12
	Date of Maximum SMD		167	202	212	239	256	262	36	32	170	197	217	238	252	271	35	35	153	156	200	218	248	258	39	37	167	203	205	243	251	275	33	32
	Wettest Week		52	17	210	200	329	350	108	136	41	62	210	191	329	330	110	110	30	6	246	202	346	350	121	145	22	5	208	172	340	353	124	153
	1st Grass Frost (Autumn)		185	257	212	279	240	305	23	20	186	258	216	275	249	297	25	16	183	239	190	263	199	287	9	20	198	260	237	287	265	309	25	19
	1st Air Frost (Autumn)		258	301	286	326	313	353	23	19	270	301	292	323	318	354	20	20	241	301	257	319	276	340	20	17	272	305	296	326	314	352	16	18
	Return to Field Capacity		260	288	283	309	313	329	23	17	253	280	278	305	302	321	21	18	235	255	263	274	288	288	22	13	245	271	269	292	295	309	20	17
	Growing Season End		310	333	331	350	355	365	18	12	307	332	331	351	356	365	19	12	301	326	324	347	354	365	21	15	316	351	343	358	364	366	19	7
Count	Air Frost	Days	51	17	69	26	90	34	17	8	49	21	70	28	85	38	18	7	78	26	93	35	108	46	14	8	42	13	62	22	83	30	15	7
	Grass Frost		176	109	197	123	212	138	14	12	175	109	196	126	214	145	14	13	208	136	224	150	242	164	14	12	159	86	178	98	192	112	14	11
	Growing Season Range		228	275	265	321	308	360	34	33	218	281	269	323	310	360	37	29	198	258	229	302	266	351	30	36	256	317	303	343	342	360	33	18
	Growing Season Length		220	283	239	299	259	315	13	13	216	282	236	297	255	312	13	11	205	274	219	285	234	301	11	12	245	307	263	318	286	332	15	11
	Access Period Range		153	181	185	214	212	246	24	24	144	177	181	211	211	234	25	24	126	143	156	175	191	199	29	23	149	167	180	201	207	231	24	24
	Access Period Length		105	155	152	187	193	215	38	27	98	143	135	180	189	206	49	26	72	94	103	125	136	161	27	28	88	139	126	172	163	206	34	23
	Dry		133	176	159	188	176	205	17	14	143	170	164	184	181	199	15	13	123	141	139	159	156	173	14	15	162	182	174	201	190	219	12	16
	Wet		190	160	206	177	232	189	17	14	185	166	202	181	222	195	15	13	210	192	226	207	242	224	14	15	176	147	191	164	204	183	12	16
	Plant Heat Stress		0	3	1	15	3	33	2	11	0	7	3	16	10	30	4	11	0	3	3	16	9	34	4	12	0	10	4	24	10	40	5	13
	Dry Soil		0	0	0	0	0	0	0	3	0	0	0	12	0	40	0	15	0	0	1	2	0	4	5	6	0	0	1	14	0	35	4	16
	Very dry soil		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Accumulated	Frost	Degree days	-87	-53	-172	-89	-283	-100	-76	-28	-89	-32	-176	-58	-267	-93	73	24	-175	-45	-268	-76	-377	-118	88	27	-80	-21	-144	-45	-228	-76	59	24
	Growing Day Degrees		1082	1846	1234	2059	1349	2262	100	170	1087	1880	1247	2083	1383	2280	104	173	908	1646	1067	1854	1193	2058	121	168	1309	2159	1474	2411	1635	2632	125	182
	Heating Day Degrees		2616	1763	1923	1763	3070	2059	164	115	2629	1784	2859	1936	3015	2076	157	118	2897	1961	3102	2133	3320	2273	175	127	2306	1516	2532	1648	2720	1765	161	105
	Excess Winter Rainfall	mm	323	412	485	521	619	635	123	87	300	296	442	408	538	521	81	81	910	1036	1211	1222	1502	1423	248	168	571	599	687	790	806	972	135	161
	Wettest Week Amount		55	68	87	86	117	116	24	19	48	52	68	72	83	94	16	17	92	106	123	138	153	175	25	33	65	96	88	126	113	158	21	38
	Max Soil Moisture Deficit		52	90	86	116	121	145	25	22	47	64	61	84	75	102	12	16	34	47	52	65	71	89	16	16	43	63	58	86	75	102	15	16
	Heatwave	Days	3	4	6	8	9	13	3	3	4	4	7	7	11	11	3	3	4	4	8	9	12	13	3	5	4	5	7	9	11	15	4	5
	Dry Spell		9	13	13	18	17	27	4	6	10	11	15	16	19	21	4	4	10	10	14	16	18	23	3	6	12	18	17	23	22	30	4	5
	Cold Spell		3	3	6	6	8	11	2	3	3	4	6	6	9	8	3	2	3	4	6	6	9	10	3	2	4	4	7	7	9	11	2	3
	Wet Spell		11	9	15	13	19	18	4	4	10	9	15	13	20	20	6	4	14	11	20	17	28	28	6	6	10	8	15	13	20	18	4	4
Indices	Precipitation Intensity		5.10	6.10	5.84	6.75	6.60	7.70	0.65	0.53	4.91	4.80	5.42	5.54	6.00	6.10	0.44	0.51	7.72	8.60	8.62	9.35	9.56	10.30	0.77	0.72	6.06	7.50	6.77	8.46	7.44	9.40	0.62	0.91
	Rainfall Seasonality		-0.22	-0.47	-0.01	-0.31	0.16	-0.13	0.15	0.14	-0.25	-0.36	-0.02	-0.22	0.14	-0.04	0.16	0.14	-0.31	-0.46	-0.09	-0.34	0.06	-0.19	0.15	0.11	-0.28	-0.56	-0.06	-0.43	0.12	-0.26	0.17	0.12
	Rainfall Heterogeneity		917	1019	1113	1238	1350	1427	176	152	756	812	966	992	1107	1173	133	144	1503	1784	1982	2150	2444	2449	390	259	1138	1307	1345	1726	1541	2231	208	336

Table13. Agro-meteorological metric 10th percentile, mean and 90th percentile values derived from observed weather data and downscaled future projection data at Auchincruive, Dunstaffnage, Prabost and Lairg.

Type	Metric	Units	Auchincruive								Dunstaffnage								Prabost								Lairg							
			10th		Mean		90th		SD		10th		Mean		90th		SD		10th		Mean		90th		SD		10th		Mean		90th		SD	
	name		Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut	Obs	Fut
Date	Growing Season Start	Day of year	5	1	31	17	65	49	26	19	1	1	38	8	86	22	32	10	11	1	55	25	94	61	33	25	28	5	75	36	111	66	34	25
	TSum200		36	29	52	35	68	49	14	7	33	25	47	32	62	45	13	7	39	36	56	40	73	46	14	4	51	38	70	49	88	63	16	9
	End of Field Capacity		80	76	95	93	108	113	12	17	81	79	98	93	114	110	15	16	87	82	104	98	128	118	17	16	89	82	108	103	133	122	17	15
	Last Air Frost (Spring)		98	53	117	79	138	104	16	22	92	51	114	78	134	109	17	25	88	24	112	49	134	83	17	21	129	75	148	101	165	126	14	19
	Last Grass Frost (Spring)		147	115	161	136	176	147	12	15	141	119	160	139	178	160	14	18	148	112	164	125	179	145	12	12	167	132	175	155	181	171	7	15
	Date of Maximum SMD		189	222	220	245	251	267	30	25	133	156	184	198	236	239	41	36	152	138	180	174	216	222	29	34	155	155	206	207	246	259	35	41
	Wettest Week		184	13	263	229	339	349	85	142	35	10	251	219	338	358	110	150	67	16	256	206	334	353	103	138	19	71	201	217	324	335	135	110
	1st Grass Frost (Autumn)		192	266	234	291	272	312	30	20	186	267	231	290	270	316	35	22	186	301	230	310	275	320	33	10	184	240	195	266	217	290	15	20
	1st Air Frost (Autumn)		278	304	300	330	321	353	18	19	285	313	306	334	327	356	19	16	290	354	314	356	333	357	15	2	243	301	263	321	286	336	24	13
	Return to Field Capacity		250	283	271	301	291	321	17	17	220	246	254	266	287	280	28	14	218	232	239	250	260	270	21	22	224	250	258	267	278	289	20	17
	Growing Season End		317	349	341	355	361	360	16	5	328	352	349	360	365	366	14	6	317	347	341	357	360	365	17	7	299	326	326	343	357	362	24	15
Count	Air Frost	Days	37	12	50	17	68	27	15	6	20	8	32	15	48	27	12	7	29	0	46	2	62	4	14	2	80	28	96	43	113	57	13	10
	Grass Frost		137	81	159	91	175	103	16	11	141	63	155	77	165	90	10	12	164	127	179	139	192	152	12	14	208	136	223	152	240	166	12	13
	Growing Season Range		269	312	310	339	346	356	30	19	265	339	312	352	347	365	33	11	239	294	288	333	346	364	38	26	212	267	251	308	303	347	41	29
	Growing Season Length		249	304	270	318	290	332	15	11	264	315	280	330	293	345	15	11	237	298	255	313	273	325	16	12	214	270	226	285	238	300	11	13
	Access Period Range		155	177	174	207	196	239	22	24	116	146	155	171	184	192	31	21	105	118	134	151	161	177	24	25	117	140	149	163	179	189	30	22
	Access Period Length		111	156	142	186	175	214	26	22	79	78	106	112	126	146	23	26	35	48	70	77	112	108	32	26	69	67	112	106	163	144	37	30
	Dry		132	153	158	169	175	182	17	14	108	119	130	136	149	153	16	15	80	71	97	87	119	102	15	15	104	117	119	133	139	151	19	15
	Wet		191	178	207	191	233	207	17	14	216	212	235	229	257	246	16	16	247	263	268	278	285	294	15	15	227	215	246	232	261	248	18	15
	Plant Heat Stress		0	6	3	19	6	34	4	12	0	8	2	19	4	27	2	10	0	0	1	0	2	0	1	0	0	6	4	13	8	22	5	6
	Dry Soil		0	0	2	1	7	0	6	5	0	0	1	2	1	5	2	7	0	0	0	0	0	0	1	0	0	0	2	1	5	4	5	3
	Very dry soil		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Accumulated	Frost	Degree days	-52	-14	-113	-35	-182	-65	49	21	-21	-10	-62	-28	-110	-52	39	17	-29	0	-79	-1	-119	-3	38	2	-161	-46	-281	-85	-414	-129	95	33
	Growing Day Degrees		1339	2111	1497	2325	1664	2507	121	166	1345	2227	1443	2393	1526	2574	86	176	1125	1380	1228	1494	1320	1598	87	97	1023	1637	1129	1787	1236	1968	96	141
	Heating Day Degrees		2233	1472	2456	1601	2696	1716	165	104	2316	1433	2427	1584	2599	1745	127	127	2575	2095	2723	2214	2845	2322	132	108	2861	2019	3026	2167	3234	2339	158	133
	Excess Winter Rainfall	mm	488	496	616	602	749	710	107	99	1062	1175	1268	1478	1577	1775	228	262	1109	1472	1411	1748	1693	2076	242	225	589	609	788	749	1007	932	170	141
	Wettest Week Amount		65	61	81	86	108	111	17	20	95	125	124	162	141	197	23	36	102	122	132	158	159	199	22	30	60	71	92	97	117	128	25	28
	Max Soil Moisture Deficit		44	92	67	122	87	145	22	24	30	38	45	50	62	67	13	11	23	23	37	34	48	43	10	8	24	34	39	45	57	60	11	10
	Heatwave	Days	3	6	6	10	9	13	3	4	3	6	7	11	11	16	3	6	3	2	7	2	12	3	3	1	3	5	7	8	12	10	3	2
	Dry Spell		10	12	15	20	20	30	4	7	9	11	15	15	20	21	5	5	7	7	11	11	14	16	4	4	8	7	11	11	16	15	3	4
	Cold Spell		4	3	6	6	10	10	3	3	3	4	5	7	10	11	3	3	3	2	6	3	8	4	2	1	3	3	7	6	11	8	3	2
	Wet Spell		12	10	19	14	26	19	6	4	17	16	29	24	40	35	13	8	19	27	36	40	59	58	16	14	18	13	25	19	33	25	8	5
Indices	Precipitation Intensity		5.22	5.90	5.97	6.59	6.78	7.20	0.54	0.49	7.60	8.70	8.45	9.64	9.27	10.70	0.69	1.00	7.10	8.10	8.09	8.77	8.90	9.70	0.89	0.62	5.20	5.60	5.91	6.35	6.66	7.00	0.58	0.57
	Rainfall Seasonality		-0.19	-0.46	0.00	-0.33	0.18	-0.18	0.15	0.12	-0.28	-0.44	-0.14	-0.30	0.08	-0.14	0.16	0.12	-0.23	-0.36	-0.08	-0.23	0.09	-0.10	0.13	0.10	-0.27	-0.26	-0.17	-0.12	-0.05	0.05	0.09	0.13
	Rainfall Heterogeneity		977	1126	1226	1346	1439	1519	180	173	1739	2118	2209	2618	2671	3245	362	507	1895	2258	2309	2763	2892	3228	424	398	1055	1124	1432	1360	1824	1636	274	210

5.4.2.1 Probability distributions.

The empirical CDF plots and probability plots for Auchincruive (Auc) representing dairying/ livestock / arable based agricultural systems and Aberdeen (Abd) representing mixed livestock / arable systems are shown in Figs. 24 and 25. At both sites all temperature driven Ag-Metrics show a substantial change to either earlier (mean of *start of growing season* by 14 days at Auc and 44 days at Abd, mean of *start of field operations (Tsum 200)* by 17 days at Auc and 20 days at Abd and mean of *last spring air frost* by 38 days at Auc and 41 days at Abd) or later (mean of *end of growing season* by 14 days at Auc and 17 days at Abd). However, the date for the *end of field capacity* shows virtually no change at either site. Conversely the date of reaching the *maximum soil moisture deficit* and *return to field capacity* both occur later (mean by 25 and 30 days at Auc, and 20 and 17 days at Abd, respectively). For *start of growing season*, *Tsum 200* and *end of growing season* at both sites, the CDF shows a shorter time-span of reaching 100 percent. The opposite is the case for the *last spring air frost*.

The probability plots (Fig. 26) for *Counts* show substantial differences in all cases except the *access period* at Aberdeen. *Plant heat stress* days increase substantially, particularly at Auchincruive, with a change in mean from 3 to 19 days. The variability of this Ag-m*et al.*so changes considerably from a concentration around 0 (45% probability at Auc and 65% at Abd) to all but three years at Abd having some years with *plant heat stress* days. However this Ag-Met does not capture the vital aspect of when the heat stress occurs, an important consideration in respect of crop development. The number of air frost days shows a substantial decrease (mean of 50 down to 17 at Auc, and 58 down to 11 at Abd), and also a reduction in variability. *Plant heat stress days*, *air frost days* and *growing degree days* are all temperature determined, whereas the *access period range* is the difference between the dates of *end of* and *return to field capacity*. Though the date for the *end of field capacity* does not change the *return to field capacity does* (Figs. 24 and 25), resulting in the longer *access period range* (change in mean by 33 days at Auc and 20 days at Abd), gained in the autumn period.

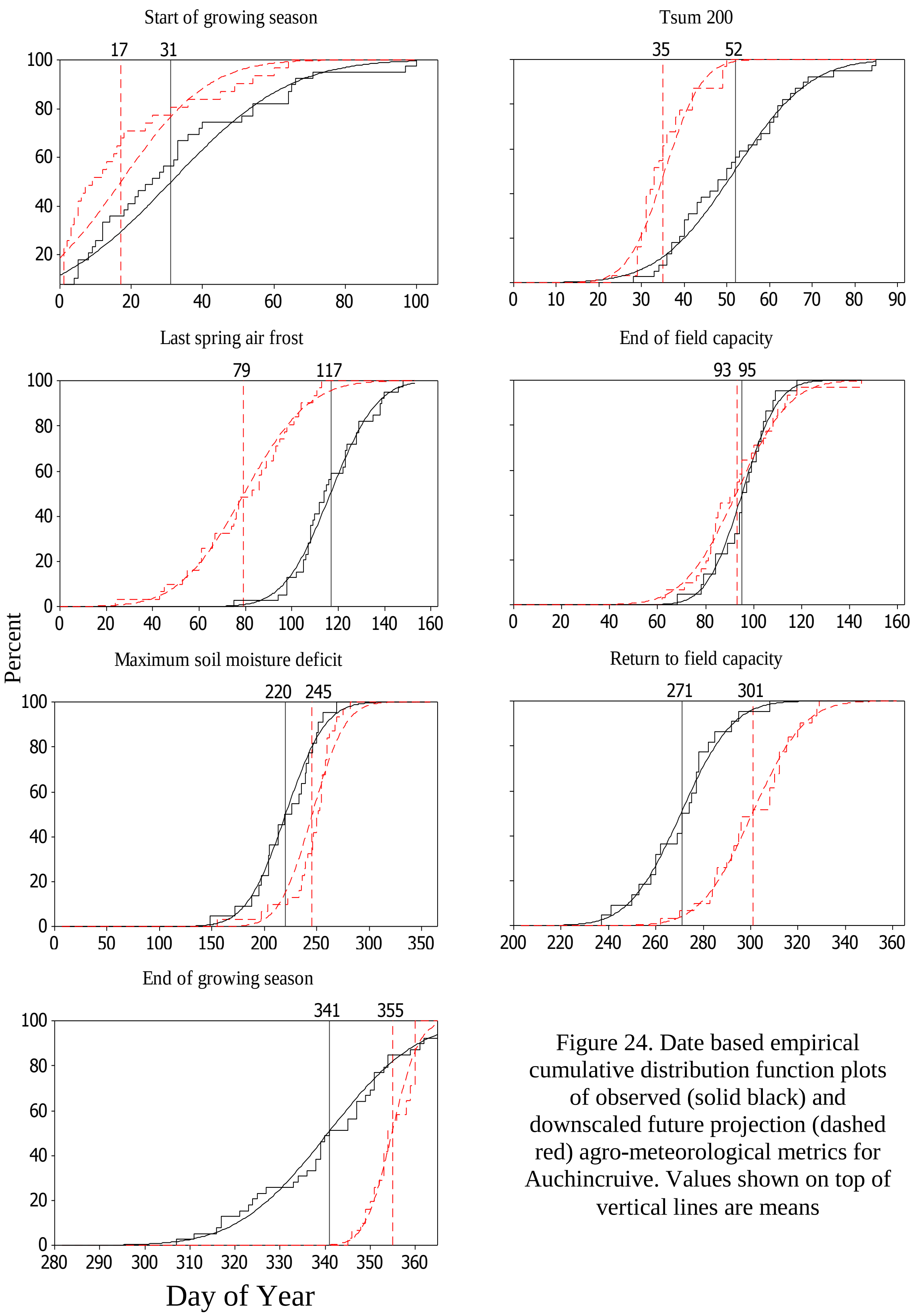


Figure 24. Date based empirical cumulative distribution function plots of observed (solid black) and downscaled future projection (dashed red) agro-meteorological metrics for Auchincruive. Values shown on top of vertical lines are means

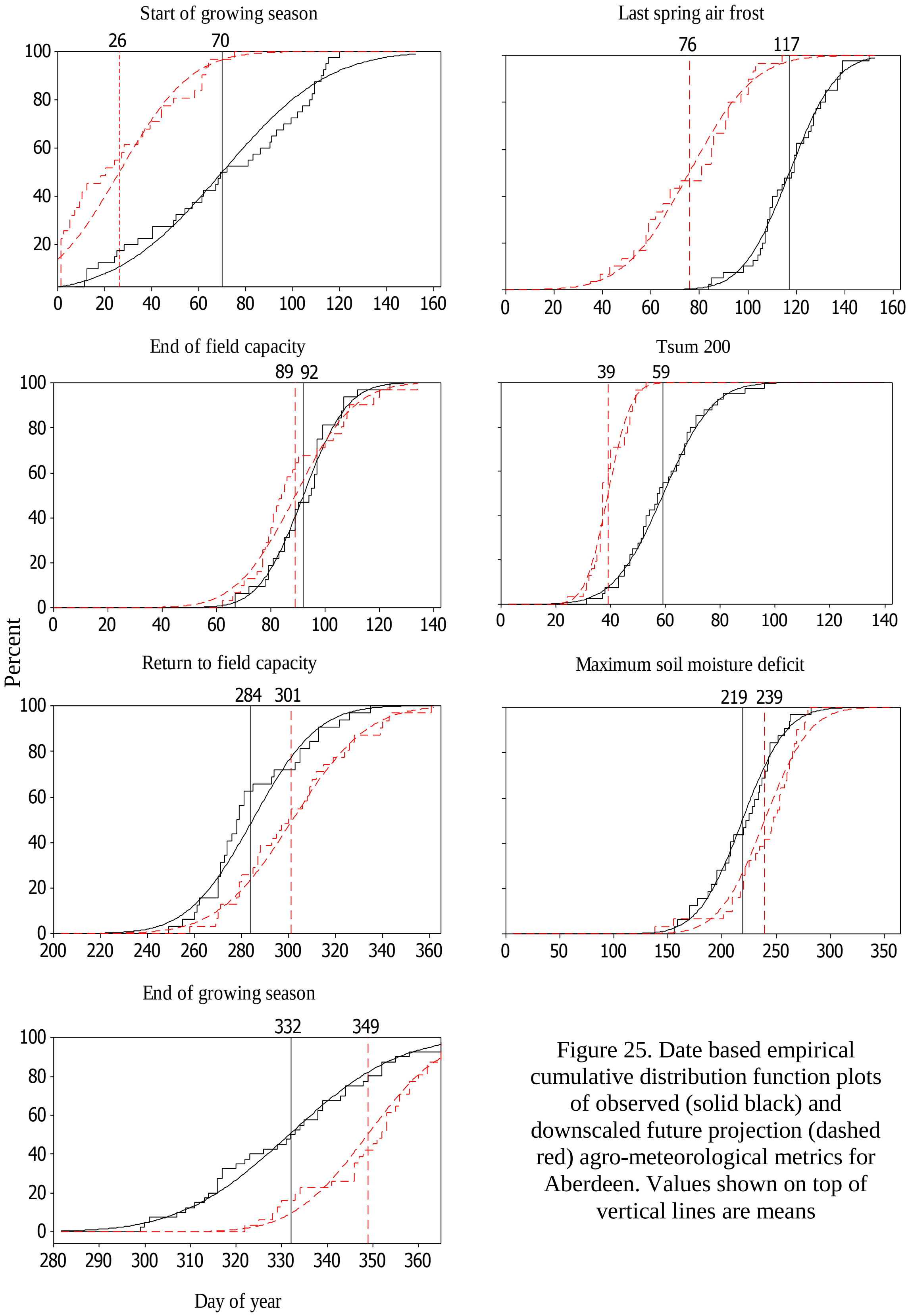


Figure 25. Date based empirical cumulative distribution function plots of observed (solid black) and downscaled future projection (dashed red) agro-meteorological metrics for Aberdeen. Values shown on top of vertical lines are means

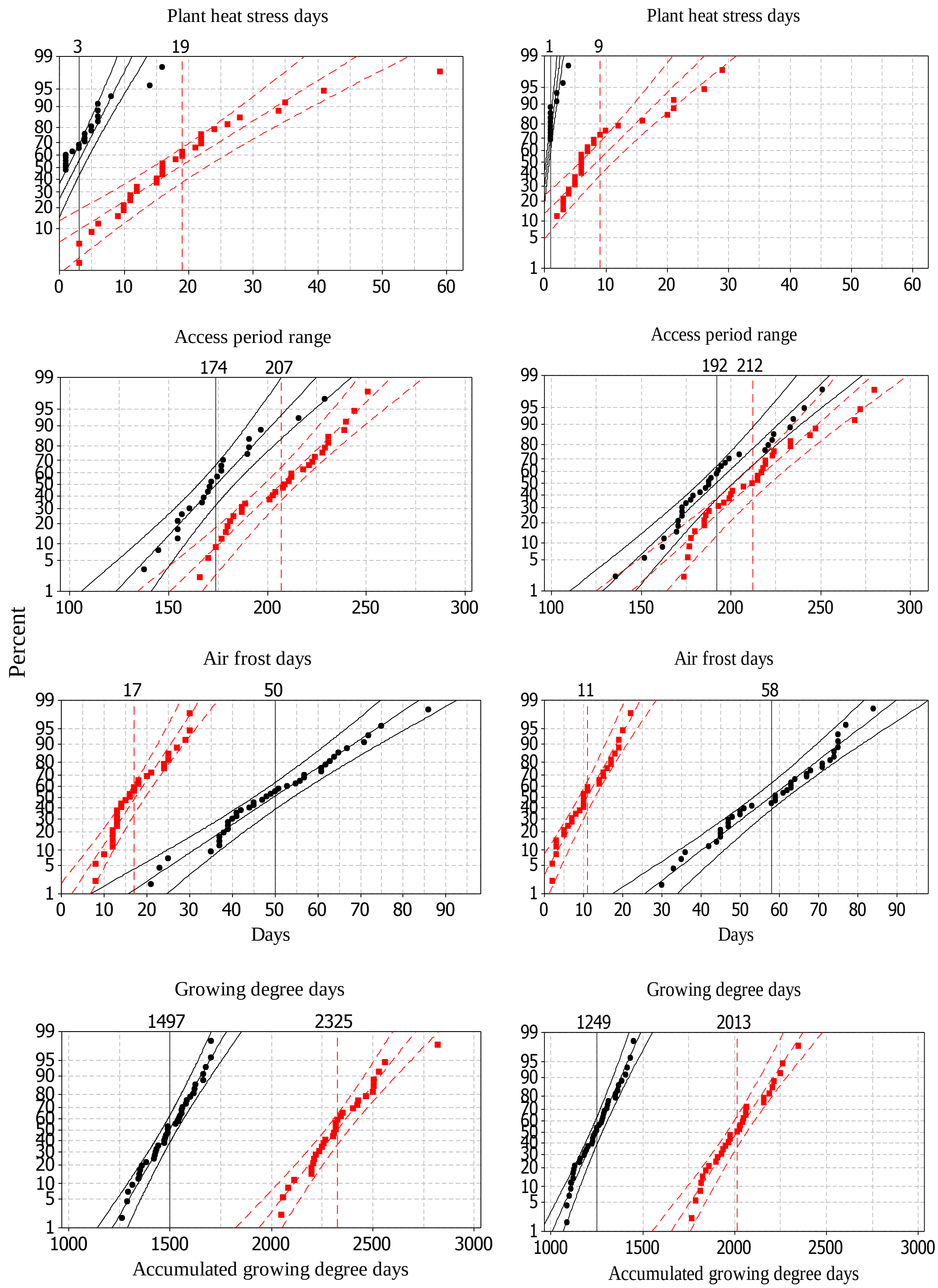


Figure 26. Probability distribution function plots of observed (black solid) and downscaled future projection (dashed red) *count* day based metrics at Auchincruive (left) and Aberdeen (right) (with 95% confidence intervals). Values shown on top of vertical lines are means.

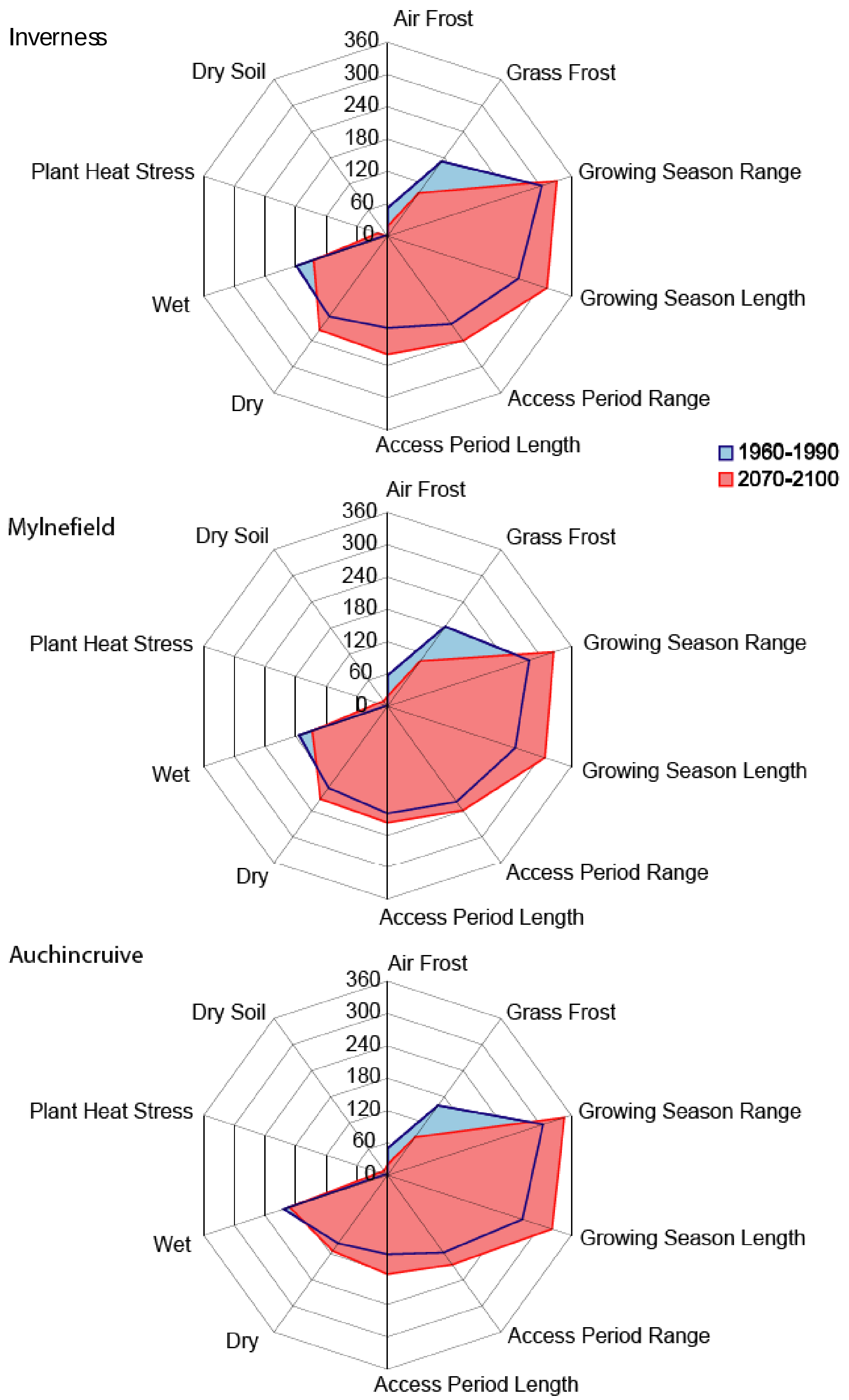


Figure 27. Single site, multiple metrics polar plots derived from observed (blue) and downscaled future projection weather data (red) at Inverness, Mylnefield and Auchincruive

5.4.2.2 Single-site with multiple metrics.

Three sites representing different farm types were chosen as examples: Mylnefield (arable / horticulture), Inverness (arable/livestock) and Auchincruive (dairying / livestock / arable). Fig. 27 shows the median values for a range of Ag-Metrics under current and downscaled future climates that are relevant to management decisions controlled by frosts, growing season, access and water. The following values, as shown in Table 11, are the means:

Mylnefield: Whilst *growing season start* and *Tsum200* are both projected to occur earlier in the year (day 58 to 25 and 60 to 39, respectively), the *end of field capacity* in spring does not change (87 to 86), but the *return to field capacity* in autumn does, coming later by approximately 20 days (297 to 317). Under the current climate *Tsum200* is generally close to *end of field capacity*. Conversely, the *end of the growing season* and *return to field capacity* become more similar, occurring later in the year. The yearly variation of this can be seen in Fig. 28. For the last *air frost* (spring), there is a shift in the mean to occur earlier in the year (day 114 to day 73), with the same happening for the last spring *grass frost* (day 161 to day 130). The increase in the *growing season range* (day 277 to 327) and *length* (250 to 312) in the future indicates an expansion at both ends of the year, which is also reflected by the increase in *access period range* (209 to 230) and *length* (187 to 206). The number of *dry* days is projected to increase from 187 to 216. In the observed period there was an average of 2 days when *plant heat stress* occurred (>25 °C), increasing to 19 days in the future, but most noticeably the 90th percentile increases from 4 to 33. Under the observed climate, Mylnefield had 4 *dry soil* days, but in the future conditions is potentially faced with a mean of 16 *dry soil* days per year the 90th percentile reaching 47.

Inverness and Auchincruive: These sites have the same pattern of changes as Mylnefield. Inverness shows an increase in the number of *dry soil* days and more marked alternation between *wet* and *dry* periods, whilst Auchincruive shows only a small change between *wet* and *dry* periods. Both sites also show a proportionally larger increase in *access period length* and *range*.

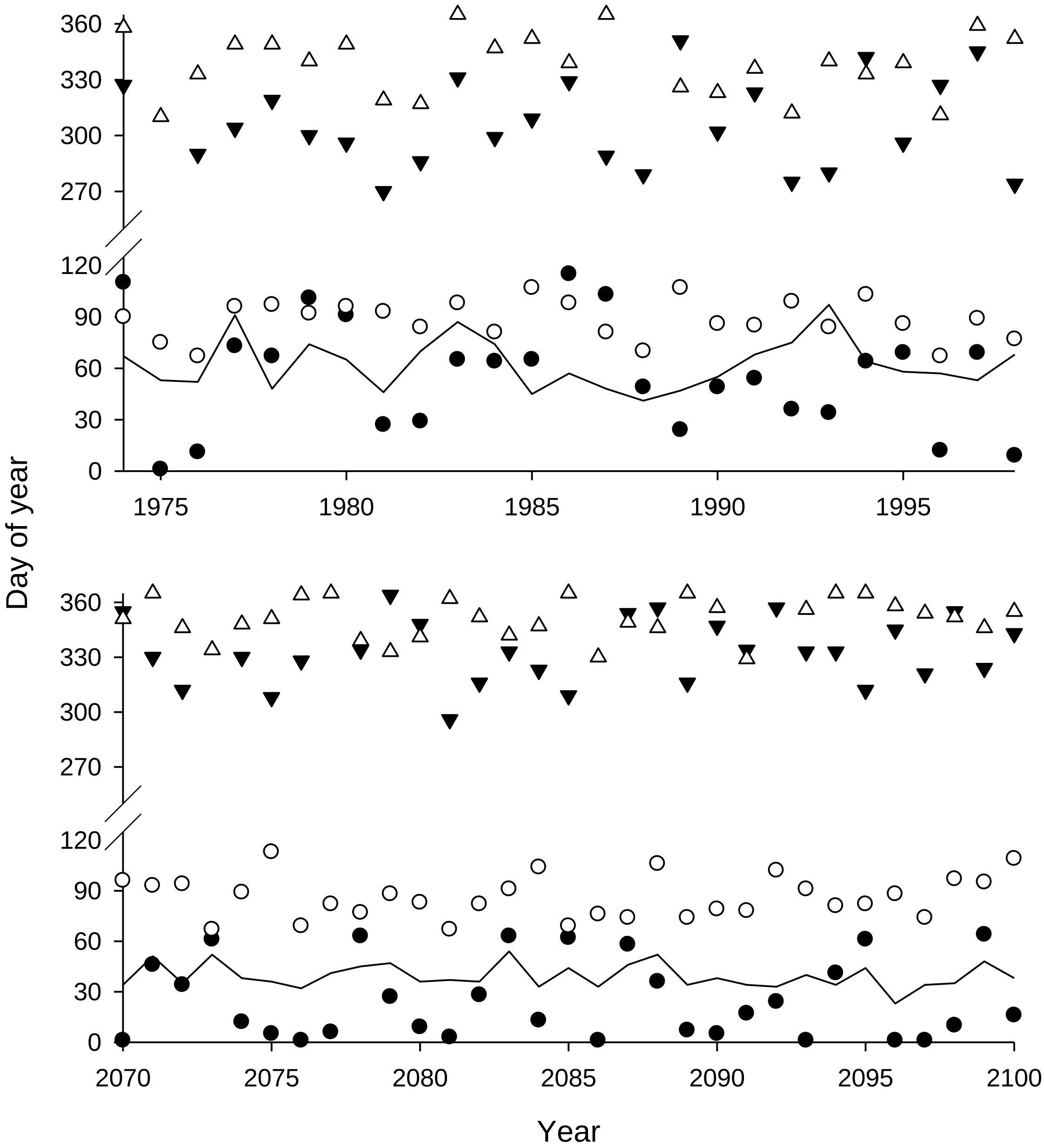


Figure 28. *Start* (●) and *end* (Δ) *of the growing season, Tsum200* (—) and *end of field capacity* (○) and *return to field capacity* (▼) at Mylnefield for 1974-98 (derived using observed S_o data only) and downscaled future projection data.

5.4.2.3 Single metric at multiple sites.

The polar plots in Figs. 29 and 30 show the median values of individual metrics, illustrating 7 locations ordered clockwise in conjunction with their geographic positions (Fig. 2, Ch 1), allowing east-west and north-south and neighbouring site comparisons. In these plots four additional sites were considered in this section: Aberdeen (arable/ general livestock), Bush (livestock/arable), Dunstaffnage (livestock) and Eskdalemuir (upland farming). Values in parenthesis below are means from Tables 11-13.

Growing season start (day of year): All seven sites show a substantial shift to an earlier start in the year, particularly Eskdalemuir (day 46). The west coast sites of Auchincruive and Dunstaffnage, and to a lesser extent Inverness, have a relatively early start under current conditions, but this shifts forward towards a point where there is virtually year-round potential growth when also considering the *end of growing season*.

Start of field operations (Tsum200): This Ag-Met is commonly used amongst farmers in the UK as an indicator of the possible start of field based operations, so may form a alternative representation of the start of the growing season. At all sites *Tsum200* is reached much earlier in the year, on average by 20 days, again with Eskdalemuir showing the furthest advancement (from day of year 74 to 49). Aberdeen, Mylnefield and Bush also show greater similarity in *Tsum200* with the g*rowing season start* day, whilst Auchincruive, Dunstaffnage and Inverness have g*rowing season start* day values approximately half those of the *Tsum200*. This reflects the occurrence of occasional mild days in the west during the early part of the year, but which do not indicate a true start of the growing season.

End of field capacity (spring): All 12 locations show only a small shift towards the *end of field capacity* being reached earlier in the year, by an average of just 3 days, with little difference between sites.

Last air frost (spring): All 12 sites show a shift towards the last spring air frost occurring earlier in the year, changing by 42 days on average across all sites, with Eskdalemuir having the largest change (49 days earlier).

Return to field capacity: All 12 sites had a shift towards later in the year in the future, by an average of 20 days, with Inverness having the largest delay of 36 days, whereas Lairg was only 9 days. The wetter western sites show fewer days delay in the *return to field capacity* than those in the east.

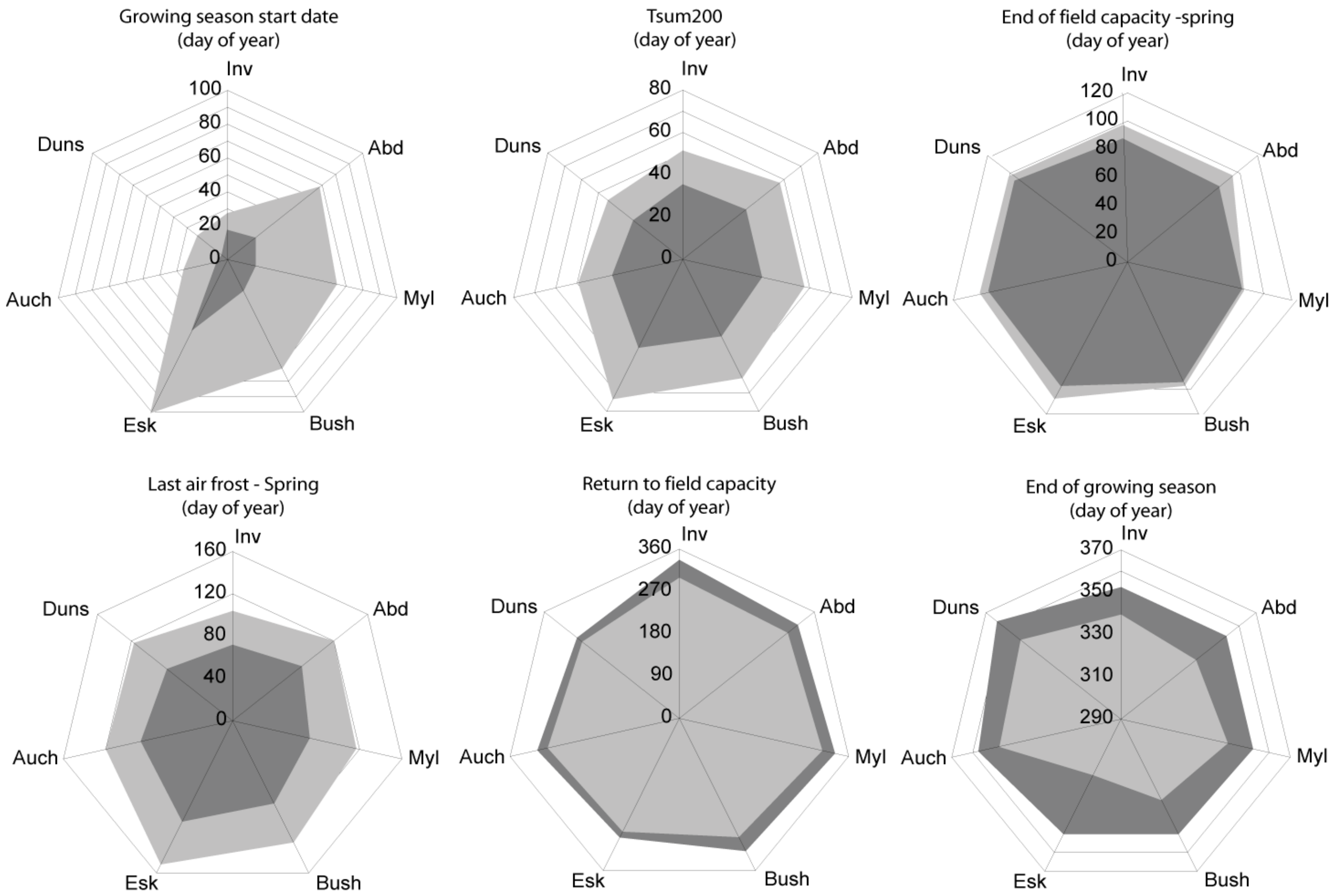


Figure 29. Single metrics at multiple sites derived from observed (light grey) and downscaled future projection (dark grey) weather data at Inverness (Inv), Aberdeen (Abd), Mylnefield (Myl), Bush, Eskdalemuir, (Esk), Auchincruive (Auc) and Dunstaffnage (Duns).

End of growing season (day of year): There was an average of 20 days delay before all 12 sites reached the e*nd of growing season* in the future, with Aviemore having the longest delay of 28 days.

The total *growing season length* (days) increases by an average 59 days, with Aberdeen and Eskdalemuir having the largest increases of 62 and 66 days respectively. However, this is influenced by the issue of the utility of the definition of start and end of growing season Ag-Metrics.

Access period length (days): This increases at all sites, by an average of 27 days, but Dunstaffnage changes by only 6 days whereas Inverness expands by 49 days.

Growing degree days: This increases by an average of 785 degree days, with the largest increase occurring at Dunstaffnage (930) and the lowest at Prabost (266).

Plant heat stress: Under the current climate there were on average only 4 days when *plant heat stress* (days > 25 °C) occurred, but under future conditions this rises to an average of 24 days. Prabost shows the lowest increase (1) whilst Dumfries has the largest (20).

Maximum soil moisture deficit amount (SMD, mm): All sites except Prabost show an increase in *maximum SMD*, the largest increase occurring in Auchincruive (55 mm) and with an overall average change of approximately 18 mm.

Excess winter rainfall (mm): There was a range of responses, with some sites (Inverness, Aviemore and Eskdalemuir) showing a decrease in *excess winter rainfall* (49, 55 and 11 mm respectively), whilst the other sites had an increase, most noticeably the large increases at Dunstaffnage (210 mm) and Prabost (338 mm). Overall the balance across all sites is an increase of approximately 46 mm.

Wet spell (days): There was little change in the *wet spell* duration, altering by an average of only two days across all sites. The *dry spell* was the same (but opposite). Similarly the *heatwave* and *cold spell* metrics did not vary by more than 4 days between the observed and future periods.

Wettest week (date) and *wettest week amount* (mm): The date on which the *wettest week* occurs spans the whole year across all sites, with it occurring earlier at 7 sites and later at 2, whilst 3 were the same. The *wettest week amount* showed a general increase (mean of 15 mm) across most sites, with the largest occurring at Dunstaffnage (38 mm), whilst other remained the same (i.e. Bush at 1 mm).

Precipitation intensity, *seasonality* and *heterogeneity* (indices): All sites showed an increase in *intensity* (mean of 0.865), the largest being at Dumfries (1.690). *Seasonality* changed, with all sites except Lairg developing wetter winters (S < -0.13), whilst the Modified Fournier Index increased at all sites accept Aviemore, with the higher values indicating the probabilities of a tendency towards increasing *heterogeneity* in yearly rainfall distribution.

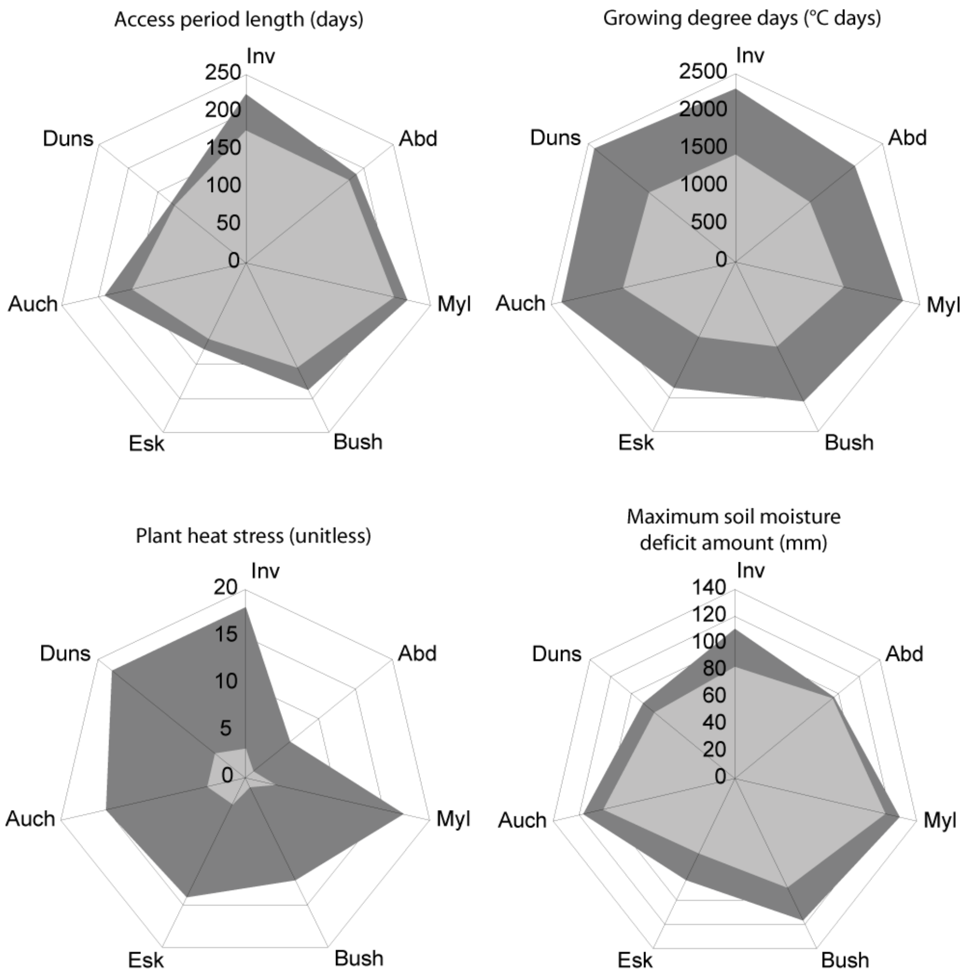


Figure 30. Metrics at multiple sites derived from observed (light grey) and downscaled future projection (dark grey) weather data at Inverness (Inv), Aberdeen (Abd), Mylnefield (Myl), Bush, Eskdalemuir, (Esk), Auchincruive (Auc) and Dunstaffnage (Duns).

5.4.2.4 Soil water balance.

Time series results from the soil water balance model for Mylnefield are shown in Figs. 31 to 33. Comparison of the driest years from the observed and future climate data (Fig. 31) shows two main differences. Firstly, the future projection has a considerable increase in the time that the soil water is below that of being available to plants. Whilst the driest observed year (1984) shows an earlier and more gradual decline in soil water, but reaching the PWP at the same time as in the future projection, the driest future year continues to decrease until October. In 1984 water became available to plants again in September. These values are also consistent with the number of *plant heat stress* and *dry soil* days in Table 11. Secondly, the date on which the future driest year reaches field capacity (FC) again in the autumn is approximately one month later than the observed driest year (a mean of 20 days for all future years). The rate of recharge is also more rapid in the future driest year, with more distinct rapid stepped increases associated with larger precipitation events. For the wettest observed (1987) and future wettest years (Fig. 32), there is little difference between the two, except the number of days, approximately in June, when the water is above FC in the future. The pattern of recharge during the summer to autumn period is different in that the observed year shows regular recharge events producing a more even level of plant available water (PAW), whilst the future has more widely spaced recharge events, reaching lower levels of PAW and recovering more sharply. Such patterns would be associated with warm temperatures and higher ET rates along with dry spells interspersed with occasional large (>100 mm) rain events. Also noticeable is the number of days when the soil is drier than FC during the spring and at the end of the year and into the next. The continuous ten year plots (Fig. 33), show nine out of ten years when soil water goes below the PWP and into a dry soil condition in the future, compared with five out of ten for the observed years. As a consequence, there are no two years in sequence when PWP is not reached in the future, compared with five consecutive years in the observed period. The future plot also indicates that the average SMD is approaching that of the driest year (1984) in the observed period.

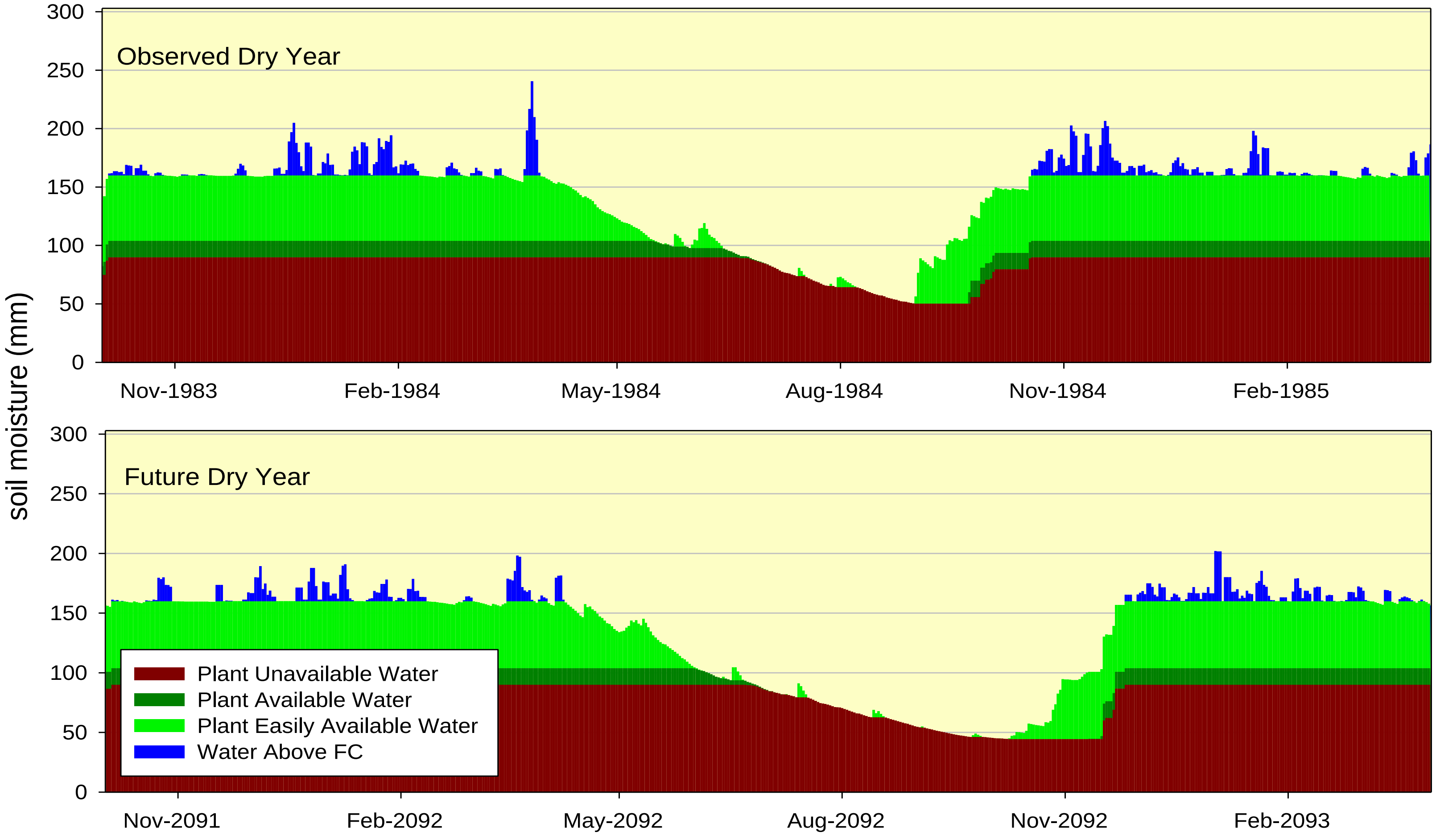


Figure 31. Soil moisture estimates from soil water balance model at Mylnefield: driest year from 1960-90 (top) and downscaled future projection (bottom). Created by K. Buchan.

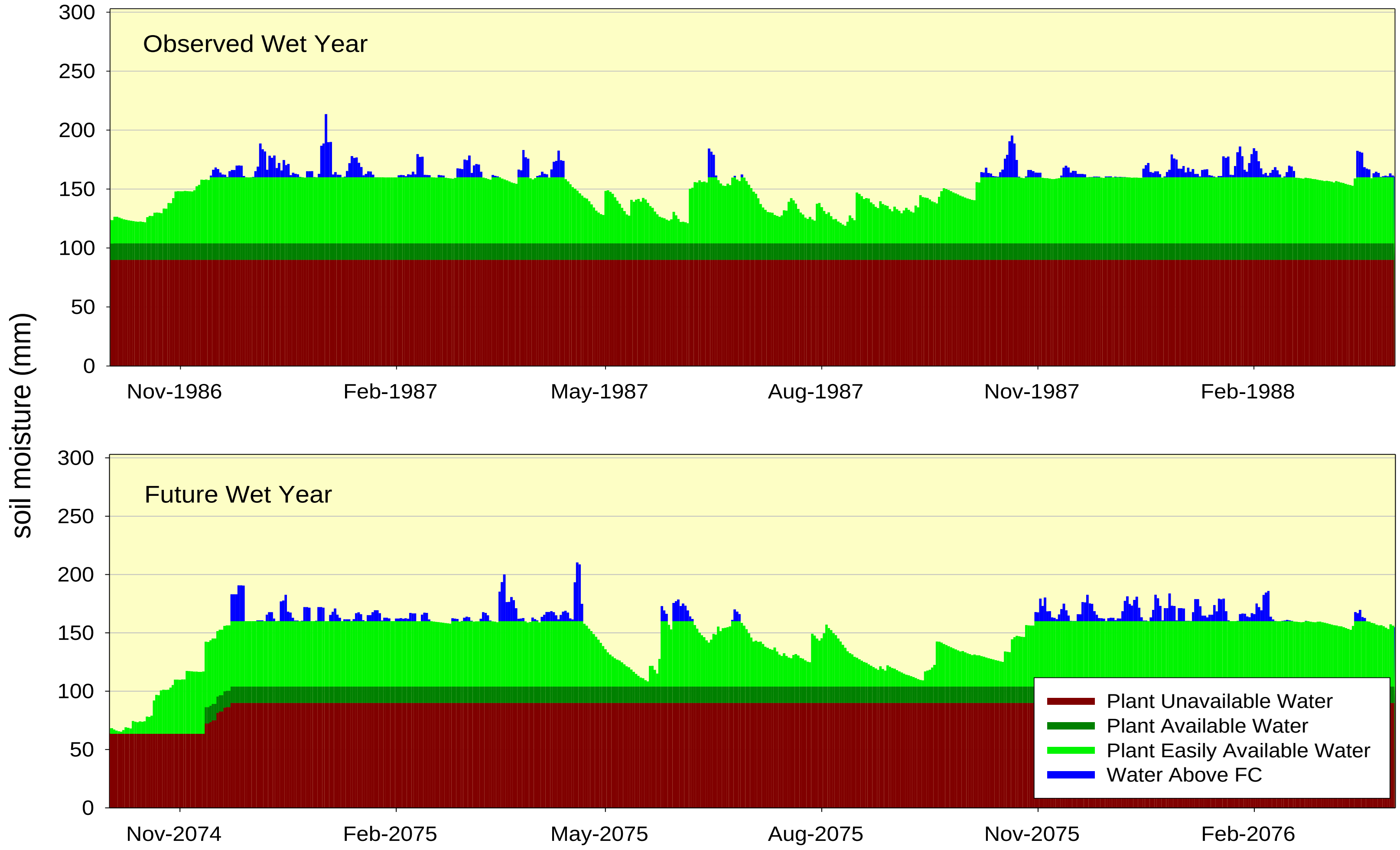


Figure 32. Soil moisture outputs from soil water balance model at Mylnefield: wettest year from 1960-90 (top) and downscaled future projection (bottom). Created by K. Buchan.

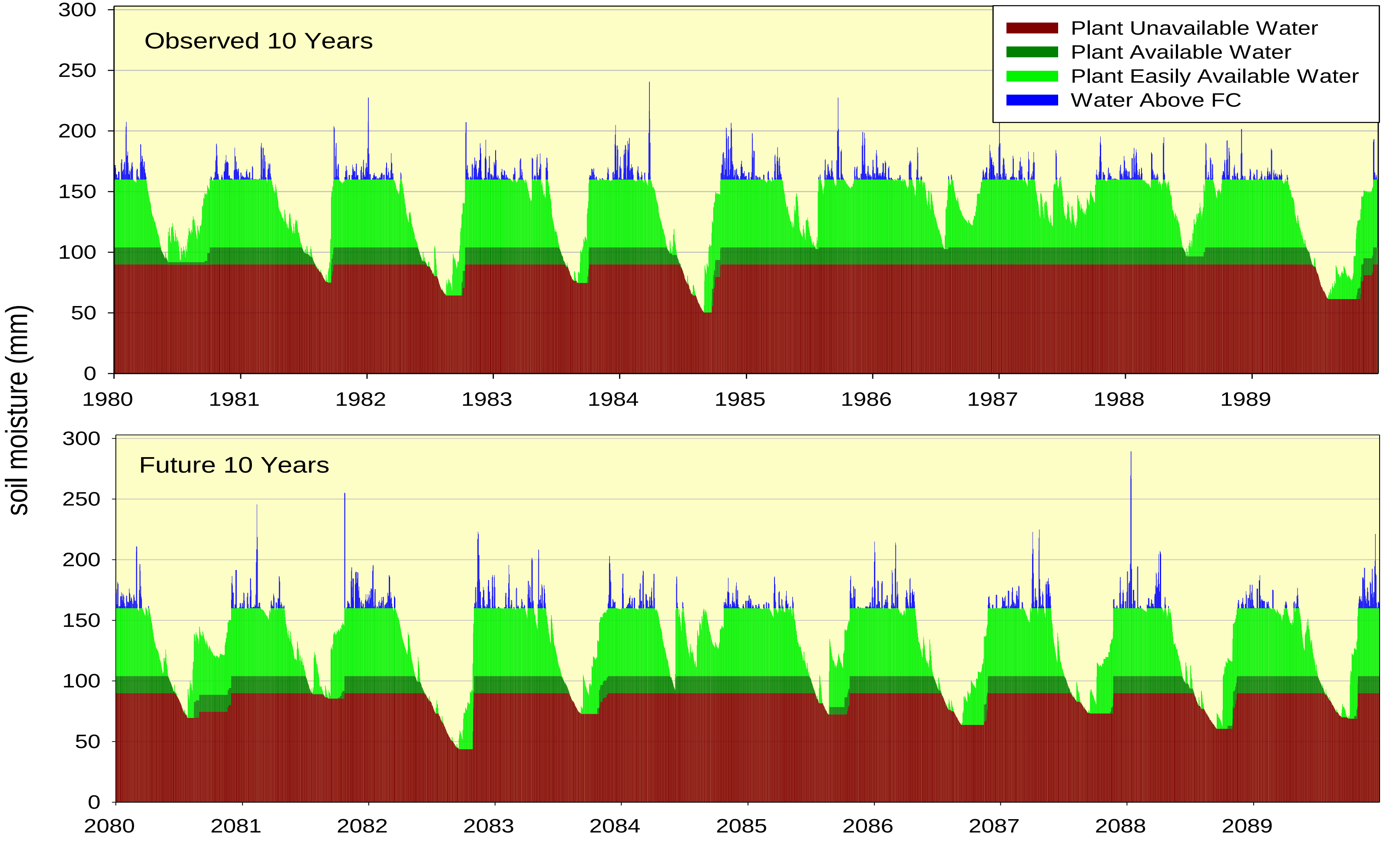


Figure 33. Continuous ten year soil moisture outputs from soil water balance model at Mylnefield 1980-90 (top) and downscaled future projection (bottom). Created by K. Buchan.

5.5 Discussion.

5.5.1 Agro-meteorological metrics.

The application of the Ag-Metrics to characterise impacts of a changed climate on weather and soil water controlled land use practices has demonstrated their potential value for planning purposes. For example, the soil water balance estimates provide information that would be of value in planning investment in irrigation systems, or the need to re-evaluate management options for soil water retention. Similarly, the indications of the potential changes to the length and timing of the growing season may enable land managers to better plan feed allocation regimes and to explore options for changing the timing of livestock calving. Further evidence of the Ag-Metrics potential for planning purposes in in the indications to the levels of risks associated with frosts, both from the point of view of reduced risk to crops vulnerable to frosts, and increased risk arising from pests and pathogens not being controlled by frosts to the same extent. Beyond agricultural systems, the information conveyed by the Ag-Metrics will be of use for hydrologists and others concerned with water management. Importantly for planning purposes, the Ag-Metrics are in forms of communication that are readily understood and interpreted by a wide range of land managers (Matthews *et al.* 2008a, McCrum *et al.* 2009).

The use of multiple Ag-Metrics allows a greater range of interactions between single values to be interpreted for a particular location. Such an approach is required in order to identify limited elements or thresholds, such as the *end of field capacity* effect on accessibility. The application process has also allowed their critical appraisal in terms of their definition and structure. For example, the *start of the growing season* may be misleading as it is possible to have five consecutive days > 5.6 °C (the definition for the *start of the growing season*), and then another long cold period afterwards in which plant growth does not occur. However, in combination with other well defined Ag-Metrics, such as *start of field operations* (*Tsum200),* it is possible to gain a clearer overall picture of when plant growth could be expected to start. An iterative process of application, stakeholder appraisal and re-development ensures increased utility of Ag-Metrics (Matthews *et al.* 2008a), which can continue in the future.

Whilst there are still large *scenario* and *representation* uncertainties associated with future projections of the climate affecting the quality of climate model estimates, the use of Ag-Metrics to characterise the potential impacts serve as key indicators of the likely conditions under which decisions will need to be made. Ag-Metrics can be estimated for a range of scenarios and from different climate models in order to establish more probable changes. This in turn provides important information as to how land management may be required to adapt in the future, and how current mitigation strategies will relate to those adaptations. The Ag-Metrics also allow the perception that climate change may be beneficial to agriculture in temperate areas to be challenged. Whilst climate change may present opportunities for agriculture in places such as Scotland, there is also a shift in the balance of risks, for example the possible increases in pest and pathogen activity, increased heat stress and potential restricted water availability. Future projections of Ag-Metrics indicate how those risks will manifest themselves, along with an indication of the frequency with which they may occur.

Useful additions to the climate summaries would be the inclusion of indications of the change in variability of the mean daily temperatures, coupled with approaches to provide information on changes in the extreme ranges. However, again the caveat must be added that the HadRM3 was found not to estimate hindcast extreme temperatures well (Chapter 3).

5.5.2 Future impacts.

The Ag-Metrics indicate a potential paradox, with an increased *length* and *range of growing season* and *start of field operation* (*Tsum200)* happening earlier in the year, but with little change in the *end of field capacity*. This implies that access to land, both by animals and machinery, may still be restricted at the start of the spring season, but access may be possible for longer in the autumn. This will have consequences on a range of management decisions such as animal turnout and housing dates, land use mixes and rotations choice, sowing and fertiliser application times etc.. Warmer conditions and earlier grass growth will have consequences on the soil nitrogen balance, especially if growth occurs whilst the soil is still at or above FC. Although this in turn will affect feed quality for livestock, an additional silage cut could be made in an extended growing season. Conversely, dry summer conditions implies that livestock may require conserved feed when grass growth is water limited in the summer, but possibly less feed in the winter when grass growth may increase. However, the accessibility limitation for winter grazing will still exist. The general shift to wetter conditions in spring and drier autumns in the east may lead to a preference for an autumn calving system for cattle. Whilst the indications are for milder winters and an earlier spring, this work has not included wind speed, so it has not been possible to indicate the impacts of wind-chill and its relationship with livestock aspects such as spring lambing mortality.

For cropping systems, the Ag-Metrics indicate that shortage of soil water will become an increasing problem. Reduced soil water availability and an increase in days when *heat stress* (stomatal closure) will occur may inhibit biomass production. This has to be considered in respect though of plant responses to elevated CO_2 and possible improved water use efficiency (Leakey *et al.* 2009). The timing of when crops become heat stressed is also critical, i.e. if at anthesis can lead to a 40% reduction in crop biomass accumulation (Wollenweber *et al.* 2003). It would also be necessary to factor in the height of the local water table in order to fully determine plant available water. Similarly, consideration has to be given to the affects of heat stress on animal welfare, water availability and the provision of shade.

There is no significant increase in solar radiation projected by the climate model that might balance the growth losses due to water shortage. This implies that crop cultivars with greater drought tolerance (water use efficiency) and slower phenological development will be required. More significantly, the shift to drier soil conditions in autumn and wetter soils in spring may alter choices in rotation composition. Autumn sowing may become preferable given the opportunity to sow in dry conditions if an earlier harvest of the previous crop is possible due to more rapid phenological development determined by the greater thermal time accumulation (*growing degree days*). The *last spring frost* occurring earlier in the year, and with a generally milder winter, raises the potential for increased horticultural production in Scotland, but will also have implications of the over-wintering survivorship of pests and pathogens, whilst warm and wet conditions will favour their dispersal.

For the soil water balance, the indications are that water limitations may restrict crop growth unless irrigation water is available at some locations in some years. The number of years in the future when the SMD falls below the PWP may double the current number, whilst the number of *dry soil* days increases considerably. Hence the indication is for a shift in the amount of risk associated with each crop type. New crop cultivars may cope with future conditions, but other crops may become non-viable leaving room for novel crops to replace them, leading to changes to rotations. These possibilities have however, to be taken in consideration of wider market lead determinants. The Ag-Metrics can also be used as initial indictors as to possible directions of change relating to soil evolution related to climate change and impact on N_2O emissions (Flynn *et al.* 2005) within the context of adaptations in land use management.

An important differentiation between the Ag-Metrics and the use of crop models to derive estimates of potential changed conditions is the level of transparency involved. Models may be perceived by stakeholders to be 'black boxes' whilst the Ag-Metrics' methods of making estimates can be more easily explained. This is an important consideration the process of building credibility, relevance and salience (after Cash & Buizer 2005, cited in Matthews *et al.* 2008a) with stakeholders. Standard crop model outputs are better at providing details about the inter-relationships between modelled processes, whereas the Ag-Metrics are limited in this scope. It is not so much that the Ag-Metrics can provide more or better information than models, but they produce estimates in a way that may be more easily understood and of relevance to practical land management decision making.

5.6 Conclusions.

Future climate and soil water balances characterised by this research show that decision makers will have to adapt to new conditions that appear on the surface to be favourable to agriculture in Scotland, but which will also have greater levels of risks associated with water restricted plant growth. The magnitude and direction of changes indicates that a substantial readjustment will be required in farm management. Changes in land capability for agriculture (and forestry), as indicated here and elsewhere (i.e. Brown *et al.*, 2008) suggest a significant change in land use in the future. The growing season may start earlier and end later in the year, but the date of the end of field capacity in spring remains the same. Access to land at the start of the growing season will thus be restricted. Soil moisture deficits increase, with longer periods when soil moisture is at levels that restrict crop growth. Milder winters and earlier frost are likely to have a positive impact on pests and pathogen survivorship and dispersal, increasing the risks to crops and livestock. Such conditions may necessitate changes to key aspects of farm level management, such as types of crops grown, livestock systems used and timing of management operations. Overall, a changing climate presents opportunities for agriculture in temperate locations such as Scotland, but also numerous threats. In order to take advantage of the opportunities and negate the threats, greater clarity is needed of the probability of future conditions. There are however consequences not just for agriculture, but also for water management and biodiversity. The scale of changes in farming systems suggested by the metrics indicates substantial alterations in the relationships between farming and biodiversity.

Whilst there are still large uncertainties associated with projecting the probabilities of future climate conditions, the approach detailed here provides a framework within which it is possible to characterise climate change scenarios in terms of impacts most relevant (on a biophysical basis) that determine land use based decision making. The use of a wide range of agro-meteorological metrics is vital in order to adequately describe future conditions and clarify the relationships between weather and soil variables that are important for decision making. These issues are important when developing appropriate mitigation and adaptation strategies, both at the land management and policy making scales. This Chapter has argued that the approach taken to provide indications of future bio-climatic conditions using the Ag-metrics has high utility, from the view of the form of communication, the range of key components represented and their relevance to land managers. Fundamentally, this research has shown the value of applying agro-meteorological metrics that will aid land use based decision making and can serve as the basis for deliberation on mitigation and adaptation options. It is also important to recognise that the level of detail in the Ag-Metrics is, necessarily, quite simple hence greater utility in their use arises from linking them to models that provide further specific detail and better represent the inter-relationships between variables. Such a partnership between methods to describe potential future bio-climatic conditions has great utility in providing both important specific details and general patterns of change.

Chapter 6: Cropping systems responses.

6.1 Abstract.

This Chapter builds upon the findings in Chapter 4 by making estimates of projected spring barley and winter wheat growth, development and yields for the current and downscaled future climate. Based on the evidence from Chapter 4 on the potential changes to crop growth under a future climate, theoretical cultivars were created within CropSyst that reflect possible adaptations through plant breeding and selection and tested under the downscaled future scenario. On the balance of evidence presented in Chapter 2 section 2.8 on the role of elevated CO_2, simulations were conducted without utilising CropSyst's CO_2 response functions. This approach was taken as considerable uncertainties remain in the ability of crop models like CropSyst to adequately represent elevated CO_2 effects on growth. Instead the aim was to explore the consequences of adaptations and responses to just the altered weather conditions, as a starting point to provide evidence for how crops might be managed under a future climate without consideration of the complexities of the interactions between growth components under elevated CO_2, and hence what the combined effect might be on whole farm systems.

6.2 Introduction.

The primary cereal crops in Scotland are spring barley and winter wheat. Whilst many other crops are commonly grown (see Table 14), these two serve as key indicators as to how changes arising from an altered climate may affect other crops and filter through to farm scale management adaptations. Whole crop harvests, with earlier harvest dates, are also used for livestock feed. A complete evaluation of the climate change impacts on cropping systems would require similar investigations into the whole range of crops grown in Scotland and potential new ones, individually and as part of rotations, but this is beyond the scope of this study.

Whilst there is evidence of crop responses to elevated CO_2 (see Chapter 2 section 2.8), there are potential issues concerning different crop model's abilities to represent these responses. In CropSyst, potential evapotranspiration is adjusted by the daily ratio of elevated reference CO_2 at 350ppm. Thus a parameter can be set that specifies the annual rate of CO_2 increase, and in the crop genetic coefficients is a parameters to specify the ratio of growth at elevated reference CO_2 to that of the baseline (i.e. 350ppm). As such this does not directly increase leaf area or determine the amount of tillering (as per Wheeler *et al.* 1996b). Further to this, there has been no direct calibration of the CO_2 responses against experiments such as FACE (Stöckle pers. comm.). This raises the question as to whether meaningful estimates can be derived from models that have only a partial representation of CO_2 processes which have not been tested against known responses. Under such circumstances it is preferable to conduct modelling studies without elevated CO_2, but instead interpret estimates like yield with the understanding that it is likely to be higher, proportional to the atmospheric CO_2 concentration, but also considering detrimental effects, such as those arising from increased ground level ozone. However, from an economic perspective, it is important to recognise that yield is only one part of the mix of factors that determines financial returns on crop production.

An important component of strategic and tactical management decision making is the timing at which specific events occur, such as sowing and harvest. Changes in the timing of management determined by crop growth and phenological development, as well as soil conditions (i.e. Fig. 26, Ch 5), are likely to alter practicalities of crop choice, levels of production and therefore overall mix of land uses within a farm. It is therefore necessary to estimate crop growth and development under a future climate in order to investigate how changes in productivity might affect crop choices and how growth characteristics determine the impacts on management options.

Table 14. Cultivated area and percentage for the main crop land uses in Scotland (claimable under the Integrated Administration Control System, IACS, in 2009).

Percent	Cultivated Area (ha)	Land Use
50.47	2744171	Rough Grazing
16.47	895556	Grass over 5 years
7.45	405050	Grass under 5 years
5.29	287375	Spring barley
1.58	85690	Winter wheat
0.82	44395	Winter barley
0.42	22964	Winter oilseed rape
0.33	17930	Ware potatoes
0.31	16928	Spring oats
0.28	15455	Fallow
0.25	13427	Seed potatoes
0.12	6661	Spring wheat
0.12	6270	Peas for human consumption
0.09	5087	Winter oats
0.09	5007	Arable silage for stock feed
0.09	4987	Turnips / Swedes for stock feed
0.09	4764	Field beans
0.05	2662	Rape for stockfeed
0.05	2510	Carrots
0.04	2230	Kale and cabbage for stock feed
0.04	2027	Protein peas
0.04	2020	Shopping turnips / swedes
0.03	1871	Maize
0.03	1824	Spring oil seed rape
	4,596,873	Total
	5,437,017	Total all claimed area (all land uses)

An altered climate may provide opportunities for changes in land use. For example, projections of the potential changes to land capability for agriculture in Scotland (Brown *et al.* 2008) indicate that land currently graded as class 4 (capable of producing a narrow range of crops, but potentially high grass yields) will have a reduced climatic constraint in the future and hence the possibility of greater diversity in the range of crops grown. This may include a shift towards more cereals if such alternative land uses, other than grass, may become more financially viable. This potential has to take into consideration any remaining biophysical constraints such as soils and topography. It is also necessary to consider the non-linearity of response by farmers to external drivers due to differing levels of farmer knowledge, experience and preference (Burton and Wilson 2006).

The purpose of this Chapter is to explore the responses by spring barley and winter wheat to the downscaled HadRM3 A2 scenario climate, so as to provide indications as to the cumulative effects of changes to the dynamics of farm-scale production so trade-offs between objectives can be investigated.

6.3 Materials and Methods.

This section details the use of CropSyst to model the response of spring barley and winter wheat to the downscaled future climate change projection from Chapter 3.

6.3.1 Crop simulation.

The parameterisation of the spring barley simulations were based on those used by Rivington *et al.* (2006b) and as detailed in Chapter 4, to represent a grain harvest. The same simulation, but with the harvest date set 3 weeks earlier (George Corsar, Hartwood Farm Manager, stated whole crop harvest was normally 2-3 week before grain harvest, pers. comm.), was used to represent a whole crop harvest for livestock feed.

A generic winter wheat simulation was also created, calibrated against the Home Grown Cereals Authority ‘winter wheat growth guide’ (HGCA 2008) to achieve guideline above- and below-ground biomass and yield production (11 t/ha), nitrogen uptake, Green Area Index (GAI), and phenological development rates and harvest dates. However, the Farm Management Handbook (SAC 2009) sets out a yield value range considerably lower (6 – 10 t/ha) than the HGCA Wheat Growth Guide, and UK level statistics indicate a mean yield of 7.8 t/ha (UK Agriculture 2009), with Scottish yields being slightly higher at about 8.1

(Scottish Government 2008). This is because the HGCA guide was aimed at farmers capable of achieving the highest yields, but in reality farmers may not conduct optimal management, and suffer yield loss due to pests and diseases and adverse weather (i.e. causing lodging). The winter wheat calibration therefore utilised the HGCA guide for phenology, nitrogen and GAI, but aimed at achieving yields more in line with observed values and at the mid-range used in the Farm Management Handbook giving a target of 8 t/ha.

Simulations were run for both crops using observed weather data, HadRM3 A2 scenario future projection (OFP) and the downscaled future projection (DsFP) from Chapter 3) for 13 sites in the UK. Though each site has unique soils, for the purposes of these simulations a generic soil was used to facilitate ease of comparisons of the climatic effects on model estimates. CropSyst's vernalisation and photoperiod functions were not used for winter wheat, as initial parameterisation efforts had resulted in unstable simulations and therefore unreliable estimates. Evidence from the evaluation of the HadRM3 (Chapter 3) indicated that whilst it was poor at estimating extreme cold (i.e. Figure 13 plot A) the hindcast data did represent minimum temperature well enough and contained sufficient cold periods so as not to prevent vernalisation (i.e. Figure 9). The downscaling process was able to improve this situation. The assumption was thus made that vernalisation requirements would be met and that the crops simulated were not constrained by photoperiod within CropSyst using the downscaled HadRM3 data. However, the issue of vernalisation is included within the discussion section.

Results from these parameter sets were tested against yield and phenology values from the HGCA and national level statistics. However, no direct testing was made of soil water or nitrogen processes. Instead outputs from the model were shown to a range of researchers at the Macaulay Land Use Research Institute to ascertain whether the estimates conformed to expectations. Where validation data is absent, such a form of expert review is seen as a viable alternative (Bellocchi *et al.* 2009). Feedback from the researchers was that for the soil water, the estimates appeared to satisfactory and conformed to expect patterns and magnitudes. Concerns were expressed on the ability of the model to adequately produce estimates of nitrogen mineralization (Lianhi Wu, pers. comm.), though this would not effect crop growth as it was supplied with sufficient nitrogen fertiliser. The lack of specific testing, i.e. using statistical methods, of the key modelled processes of soil water and nitrogen does however add to the potential range of uncertainty associated with the CropSyst estimates of crop growth.

A further set of simulations for the downscaled future climate were run using the spring barley and winter wheat parameterisations that had adjustments made to the phenology parameters, representing an Adapted Future Cultivar (AFC). These adjustments were aimed at representing potential adaptations to the crops' phenological development rates, so as to maintain current timings of management operations. Adjustments were based on interpretation of the estimates made using the parameterisations and DsFP data (Chapter 4), where the date of growth stages were seen to be earlier in the year due to increased thermal time accumulation (Figs. 21 and 22, Ch 4).

Beyond the physiological impacts of a changed phenological development rate, the parameters also determine when management operations are performed. Table 14 details the changes to the parameters. The sowing date remained the same. The target for these adjusted parameters was that the harvest date would be approximately the same under the future climate, thus the crop has about the same length of time to accumulate biomass as under the current climate.

Table 14. Adjustments made to CropSyst crop parameters to represent potential adaptations to phenological development.

Phenological development parameter (growing degree days)	Spring barley		Winter wheat	
	Generic	Adapted	Generic	Adapted
Begin flowering	800	1100	485	785
Reach peak Leaf Area Index	1050	1350	820	1120
Reach maximum root depth	800	900	600	900
Begin grain filling	950	1250	605	905
Leaf duration	950	1050	890	1190
Reach physiological maturity	1300	1600	1265	1565

In respect of crop responses to elevated atmospheric CO_2, for the reasons given in Chapter 2 section 2.8, future time period simulations were run without including CropSyst's CO_2 atmospheric concentration response function.

6.4 Results.

6.4.1 Spring Barley: Grain Harvest.

As shown in Chapter 4, there are substantial differences in estimates made by CropSyst due to the weather data input source. Figure 34 illustrates this for spring barley yield estimates made at Bush (a site where the original hindcast data and downscaled data both matched well to the yields based on observed weather data). Use of the HadRM3's original future projection (OFP) estimates for the 2070-2100 A2 scenario resulted in a substantial reduction in yields (mean of 6.64 t ha^{-1}) compared with the estimates made using observed weather data (mean of 7.86 t ha^{-1}) (Table 15). Downscaled future projection (DsFP) weather data showed an improvement (to a mean of 7.20 t ha^{-1}), but still 0.66 t ha^{-1} less than the observed.

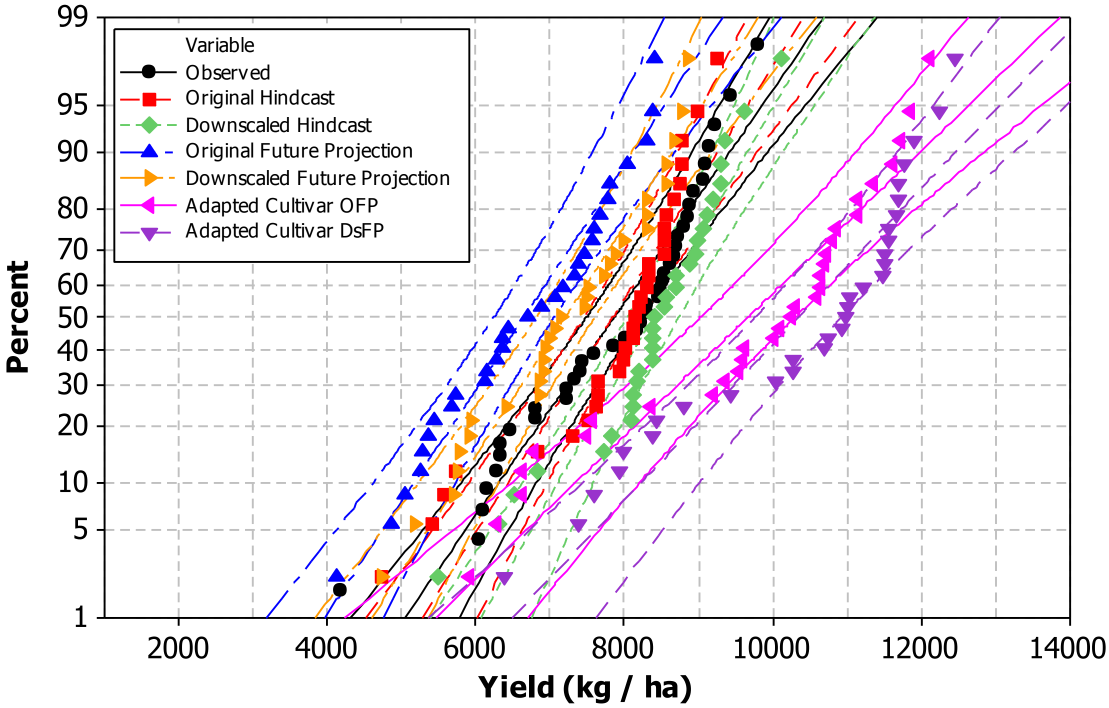
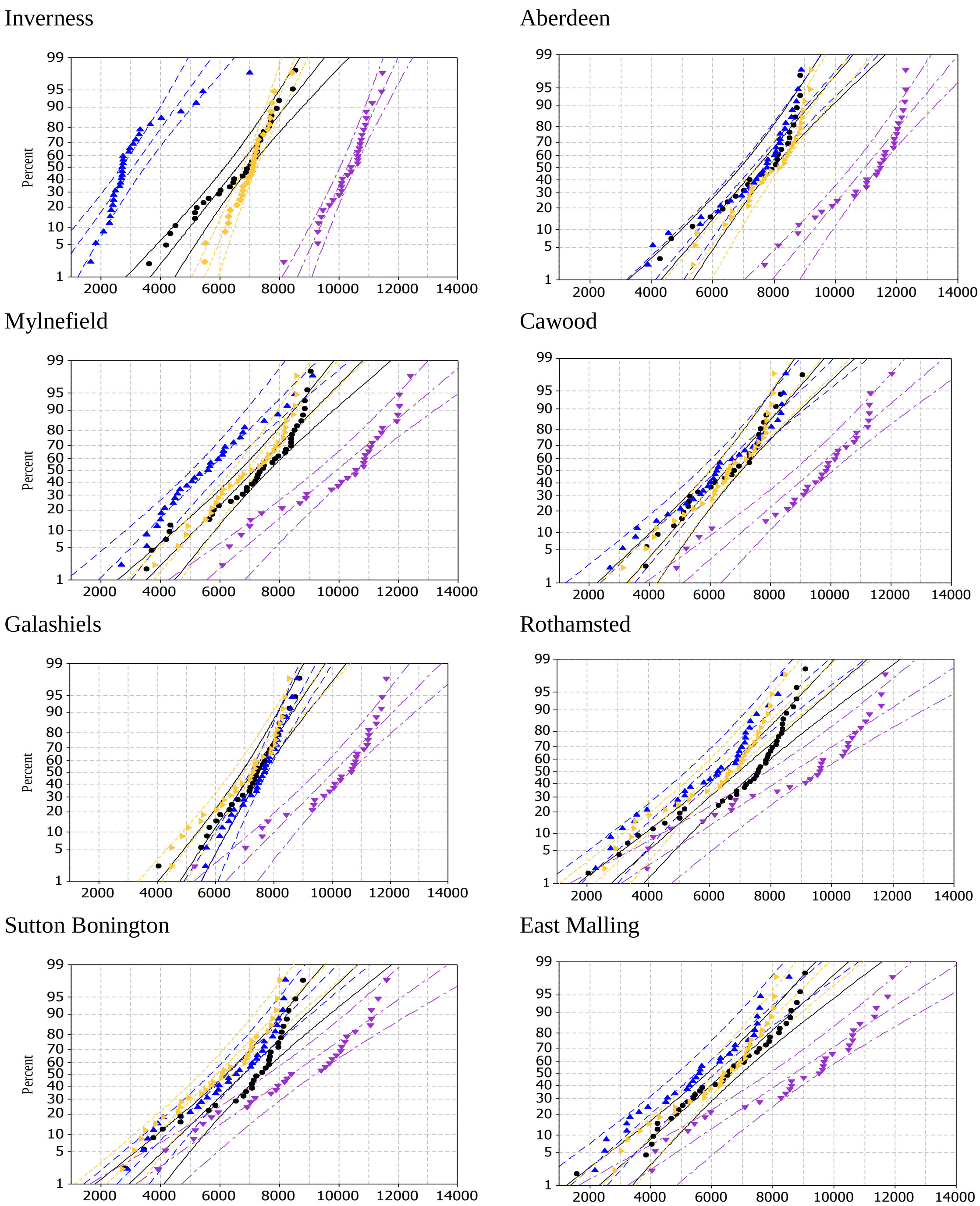


Figure 34. Probability distribution function plots of spring barley yield estimated by CropSyst using all weather data sources at Bush, plus estimated yield based on potential cultivar adaptations to phenological development using non-downscaled and downscaled future projection weather data. Lines indicate 95% confidence intervals.

The adapted future cultivar (AFC) however showed a marked increase in mean yield with both the OFP (to a mean of 8.64 t ha^{-1}) and DsFP (to a mean of 9.32 t ha^{-1}). The probability distribution is seen to be more in the higher yield ranges. The patterns of response seen at Bush are similar to those at other sites in the UK (Table 15 and Figure 35). Only at Auchincruive was there a decrease in yield from the AFC. Across all sites, the mean yield increased from the observed 6.93 t ha^{-1} to 8.47 t ha^{-1} using the DsFP data and AFC. The range in estimate values (minimum, maximum and standard deviation) for estimates from both observed and DsFP are excessively large.

Table 15. Spring barley yield estimates from CropSyst derived using observed (Obs), original hindcast (OH), downscaled hindcast (DH), original future projection (OFP) and downscaled future projection (DsFP) weather data sources, plus estimates for an adapted future cultivar using OFP and DsFP. Greyed areas indicate estimate differences less than those derived from observed weather data.

		Yield (t/ha) per data source							Yield differences (t/ha) per data source					
							Adapted cultivar						Adapted cultivar	
		Obs	OH	DH	OFP	DsFP	OFP	DsFP	OH	DH	OFP	DsFP	OFP	DsFP
Aberdeen	Mean	7.38	7.99	8.35	7.31	7.83	9.70	10.82	0.61	0.97	-0.07	0.44	2.32	3.44
	St Dev	1.92	1.77	1.22	1.37	1.13	2.11	1.93	-0.15	-0.70	-0.55	-0.79	0.19	0.01
	Min	3.42	2.97	4.01	3.89	5.37	6.46	7.23	-0.45	0.58	0.47	1.95	3.04	3.81
	Max	10.20	10.00	9.76	8.90	9.22	14.01	13.96	-0.20	-0.44	-1.30	-0.97	3.82	3.76
Auchincruive	Mean	7.51	7.16	7.70	7.38	6.95	9.53	7.14	-0.35	0.19	-0.13	-0.55	2.02	-0.37
(cell 4694)	St Dev	1.56	1.13	1.22	0.72	1.16	1.08	1.49	-0.44	-0.34	-0.84	-0.40	-0.48	-0.07
	Min	3.72	5.39	4.26	5.63	4.38	6.86	3.63	1.67	0.54	1.90	0.66	3.14	-0.09
	Max	9.36	9.20	9.20	8.42	8.71	11.43	9.35	-0.17	-0.17	-0.94	-0.65	2.06	-0.02
Bracknell	Mean	6.66	7.61	7.13	6.15	5.86	8.13	7.64	0.95	0.47	-0.51	-0.80	1.47	0.98
	St Dev	1.64	1.29	1.37	1.71	1.70	1.87	1.82	-0.35	-0.28	0.07	0.06	0.23	0.18
	Min	1.36	4.21	3.62	2.71	2.52	4.69	3.94	2.86	2.26	1.35	1.16	3.33	2.58
	Max	8.75	8.87	8.54	8.55	8.17	11.64	11.12	0.12	-0.21	-0.20	-0.58	2.89	2.37
Bush House	Mean	7.86	7.84	8.38	6.64	7.20	8.64	9.32	-0.02	0.52	-1.22	-0.66	0.78	1.46
	St Dev	1.23	1.10	0.99	1.15	1.12	1.86	1.99	-0.12	-0.23	-0.07	-0.11	0.64	0.76
	Min	4.19	4.73	5.48	4.13	4.72	6.23	6.30	0.55	1.29	-0.05	0.53	2.05	2.11
	Max	9.80	9.26	10.12	8.40	8.86	12.95	14.18	-0.54	0.32	-1.40	-0.94	3.16	4.38
Cawood	Mean	6.52	6.61	7.09	6.23	6.50	8.39	8.65	0.09	0.57	-0.29	-0.03	1.87	2.13
	St Dev	1.41	1.78	1.47	1.67	1.38	2.07	2.03	0.37	0.06	0.26	-0.03	0.66	0.62
	Min	3.86	2.58	2.95	2.67	3.10	5.27	5.34	-1.28	-0.92	-1.19	-0.77	1.41	1.47
	Max	9.06	8.82	8.99	8.51	8.12	13.06	12.69	-0.24	-0.08	-0.55	-0.94	4.00	3.62
East Malling	Mean	6.40	6.38	7.45	5.48	6.13	7.47	8.03	-0.02	1.06	-0.92	-0.26	1.08	1.63
	St Dev	1.76	1.81	1.43	1.77	1.60	1.88	2.12	0.05	-0.33	0.01	-0.16	0.12	0.36
	Min	1.58	2.53	3.40	2.18	2.81	4.36	4.15	0.96	1.82	0.60	1.24	2.78	2.57
	Max	9.05	9.15	8.77	8.52	8.11	11.59	11.89	0.09	-0.28	-0.53	-0.95	2.53	2.84
Everton	Mean	6.48	7.32	7.23	6.00	5.90	7.95	7.89	0.84	0.76	-0.48	-0.58	1.47	1.41
	St Dev	1.99	1.67	1.73	1.67	1.72	1.82	1.87	-0.32	-0.26	-0.32	-0.27	-0.17	-0.12
	Min	1.40	3.90	3.74	2.78	2.69	4.40	4.34	2.51	2.34	1.38	1.30	3.00	2.94
	Max	9.19	9.33	9.16	8.70	8.76	11.37	11.52	0.14	-0.02	-0.48	-0.42	2.18	2.33
Galashiels	Mean	7.28	7.82	8.31	7.49	6.99	9.73	8.97	0.54	1.03	0.21	-0.29	2.45	1.69
	St Dev	1.08	1.12	1.19	0.85	1.21	1.68	1.87	0.04	0.11	-0.23	0.14	0.60	0.79
	Min	4.05	4.69	4.98	5.66	4.48	6.50	5.43	0.64	0.93	1.60	0.43	2.45	1.38
	Max	8.90	9.24	10.01	8.83	8.54	12.29	12.77	0.34	1.11	-0.07	-0.36	3.39	3.87
Inverness	Mean	6.60	2.60	8.35	3.08	7.02	5.25	9.58	-4.00	1.76	-3.51	0.42	-1.34	2.98
	St Dev	1.26	0.93	1.61	1.14	0.65	1.19	1.15	-0.33	0.35	-0.12	-0.61	-0.07	-0.11
	Min	3.65	1.27	4.11	1.66	5.51	3.39	7.35	-2.38	0.46	-1.99	1.86	-0.26	3.70
	Max	8.57	5.45	10.56	7.02	8.45	8.73	11.28	-3.11	1.99	-1.55	-0.11	0.17	2.71
Mylnefield	Mean	7.17	2.49	7.70	5.61	6.88	7.66	9.01	-4.68	0.53	-1.56	-0.29	0.49	1.84
	St Dev	1.57	0.90	0.74	1.59	1.33	1.67	2.06	-0.67	-0.82	0.02	-0.23	0.11	0.50
	Min	3.54	1.23	5.21	2.70	3.82	5.17	5.38	-2.32	1.67	-0.84	0.27	1.63	1.83
	Max	9.08	5.27	8.56	9.12	8.59	11.82	13.34	-3.82	-0.52	0.04	-0.49	2.74	4.25
Rothamsted	Mean	6.97	6.99	7.49	5.85	6.19	7.78	8.17	0.03	0.53	-1.12	-0.78	0.82	1.21
	St Dev	1.81	1.53	1.26	1.75	1.70	1.93	2.08	-0.28	-0.55	-0.06	-0.11	0.13	0.27
	Min	2.04	3.09	3.68	2.27	2.56	4.31	4.31	1.06	1.64	0.24	0.52	2.27	2.28
	Max	9.13	8.74	8.90	8.43	8.46	12.16	12.25	-0.39	-0.23	-0.70	-0.67	3.03	3.11
Sutton	Mean	6.80	7.64	7.11	6.25	5.89	8.46	7.78	0.85	0.32	-0.55	-0.91	1.66	0.98
Bonington	St Dev	1.65	1.10	1.31	1.60	1.59	2.09	2.05	-0.55	-0.34	-0.05	-0.07	0.44	0.40
	Min	2.80	4.44	3.17	2.89	2.71	5.58	4.74	1.64	0.38	0.10	-0.08	2.78	1.94
	Max	8.83	9.04	8.82	8.22	8.02	13.00	12.28	0.21	-0.01	-0.61	-0.81	4.17	3.45
Wallingford	Mean	6.41	7.43	6.78	5.92	5.51	7.86	7.13	1.01	0.37	-0.50	-0.91	1.45	0.72
	St Dev	1.67	1.31	1.43	1.72	1.62	1.80	1.70	-0.35	-0.23	0.05	-0.04	0.13	0.04
	Min	1.45	4.56	3.72	2.48	2.29	4.39	3.79	3.11	2.27	1.03	0.84	2.94	2.33
	Max	8.94	8.91	8.72	8.42	8.02	11.55	10.46	-0.03	-0.22	-0.51	-0.92	2.61	1.52
	Mean	6.93	6.61	7.62	6.11	6.53	8.20	8.47	-0.32	0.74	-0.88	-0.39	1.21	1.71
	St Dev	1.58	1.34	1.31	1.44	1.38	1.77	1.86	-0.24	-0.27	-0.14	-0.20	0.19	0.28
	Min	2.85	3.51	4.03	3.20	3.61	5.20	5.07	0.66	1.17	0.35	0.76	2.35	2.22
	Max	9.14	8.56	9.24	8.46	8.46	11.97	12.08	-0.58	0.10	-0.68	-0.68	2.83	2.94



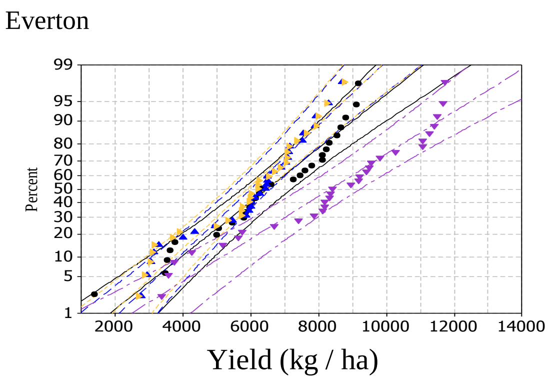


Figure 35. Probability distribution functions of spring barley yield estimates using observed and future projection data. Dashed lines are 95% confidence intervals. Observed = Black ●
Original Future Projection = Blue ▲
Downscaled Future Projection = Gold ▶
Adapted DsFP = Purple ▼

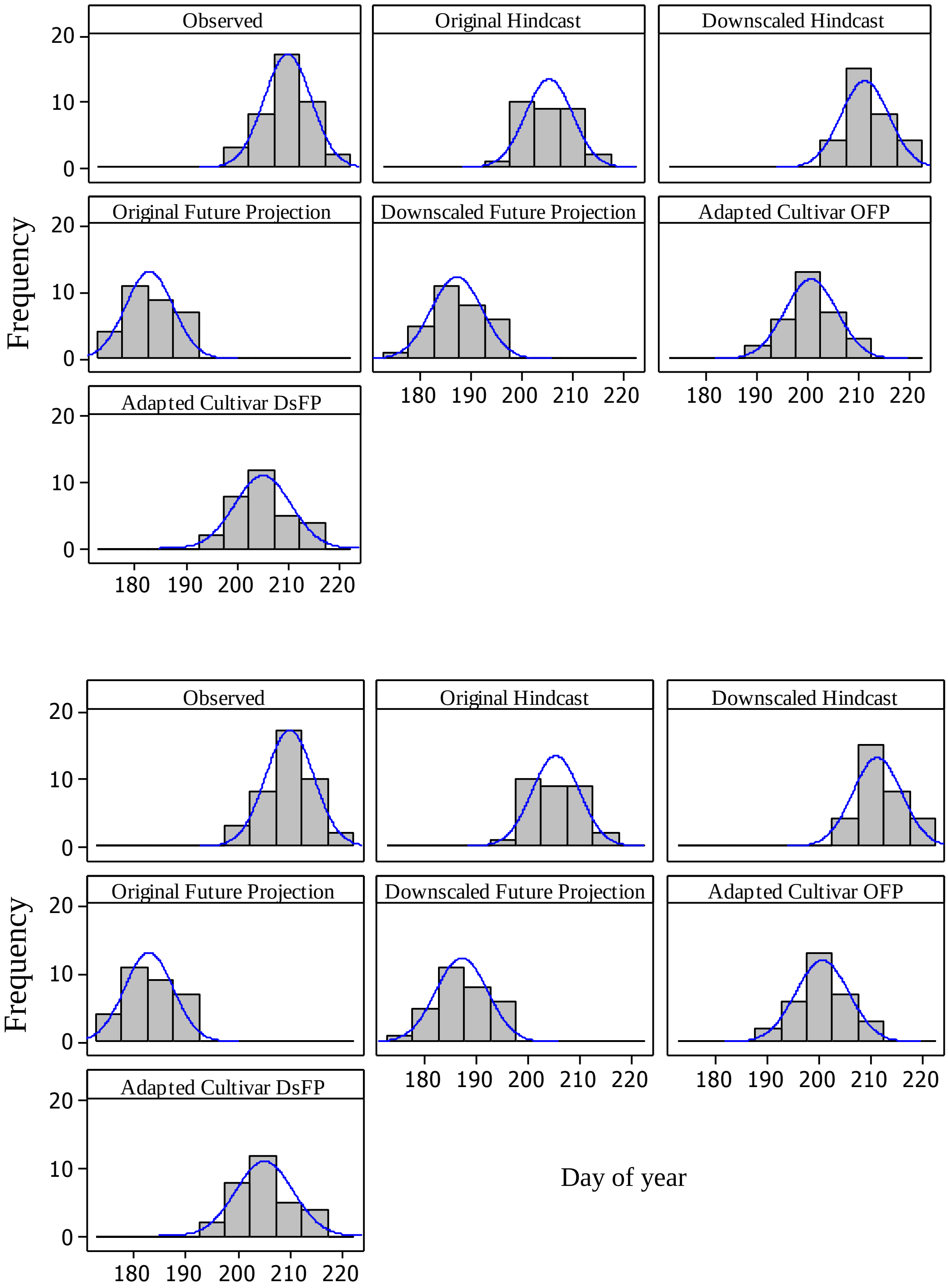


Figure 36. Day of year when spring barley begins flowering (top) and reaches physiological maturity for all weather data sources at Bush, plus estimated day of physiological maturity based on potential cultivar adaptations using non-downscaled (OFP) and downscaled future projection (DsFP) weather data. NB. Observed n = 40, all others n = 31.

Figure 36 illustrates the changes in phenological development (day of year the crop starts flowering and reaches physiological maturity) with each weather data source and consequences of using the AFC at Bush. Downscaling the hindcast weather data improves the match with estimated maturity date derived from observed weather data. The mean day of year that the crop starts flowering using observed weather data was 173, with the DsFP being 154 (19 days earlier), but this was changed to the AFC being only two days later (175) (Table 16). Using the DsFP, the crop reached maturity 23 days earlier than using the observed weather data. The AFC resulted in maturity being 5 days earlier, hence the AFC crop had a similar time period for biomass accumulation as with the crop estimated using observed weather data. The patterns of response seen at Bush (Fig. 36) were similar across all sites tested. Using the mean across all sites, the DsFP crop reached maturity 22 days earlier than the Obs (Table 16), which was reduced to 4 days by the AFC.

Table 16. Phenological development dates (day of year) derived from different weather data sources, plus estimates for the adapted future cultivar.

		Begin flowering (day of year)						Physiological maturity (day of year)					
		Obs	OH	DsH	OFP	DsFP	AFC	Obs	OH	DsH	OFP	DsFP	AFC
Aberdeen	Mean	174	175	174	155	153	175	211	213	211	189	188	206
	St Dev	4	4	4	4	4	5	4	5	4	5	5	5
	Min	165	167	166	146	144	165	201	205	203	178	177	195
	Max	181	184	182	162	161	183	217	221	220	196	195	215
Auchincruive	Mean	166	173	166	154	148	168	201	210	201	187	181	199
	St Dev	4	4	4	4	4	5	4	5	5	5	5	5
	Min	158	163	156	145	140	157	192	199	190	175	170	188
	Max	173	181	175	161	156	175	210	219	209	196	188	209
Bracknell	Mean	159	159	160	142	143	161	192	191	193	171	172	187
	St Dev	5	5	5	4	4	5	5	5	5	5	6	6
	Min	150	153	154	131	132	152	182	183	184	160	160	175
	Max	167	169	170	150	151	168	201	201	203	179	180	196
Bush	Mean	173	170	174	151	154	175	210	205	211	183	187	205
	St Dev	5	4	5	4	4	5	5	5	5	5	5	6
	Min	163	162	166	143	145	166	199	197	203	174	177	194
	Max	181	178	183	159	161	183	219	213	219	190	195	217
Cawood	Mean	162	165	163	147	146	165	196	198	198	177	176	193
	St Dev	5	5	5	4	4	5	5	5	5	5	5	5
	Min	148	158	156	135	134	155	184	188	188	166	165	182
	Max	170	174	173	154	152	173	203	207	207	186	185	202
East Malling	Mean	157	157	158	140	141	159	189	188	190	168	170	185
	St Dev	4	5	5	4	4	5	5	5	5	5	5	6
	Min	149	151	152	129	130	149	180	181	183	158	159	174
	Max	167	167	168	148	149	166	201	197	200	176	178	193
Everton	Mean	156	160	158	143	141	159	189	191	191	171	170	185
	St Dev	5	4	5	4	4	5	5	5	5	5	5	6
	Min	148	152	150	131	130	150	181	183	183	161	160	175
	Max	165	168	168	151	149	166	198	200	200	178	178	195
Galashiels	Mean	174	170	178	154	154	175	210	205	216	187	187	205
	St Dev	5	4	5	5	5	5	5	5	5	5	5	6
	Min	164	162	169	145	145	165	201	197	206	177	177	193
	Max	182	178	186	162	162	184	219	213	224	197	196	217
Inverness	Mean	165	172	166	153	148	168	201	206	201	185	181	199
	St Dev	4	5	5	5	4	5	4	5	5	5	5	5
	Min	157	164	158	144	139	156	193	195	190	174	170	188
	Max	174	183	177	161	155	176	210	216	211	194	189	209
Mylnefield	Mean	167	172	166	151	149	169	203	206	201	182	181	198
	St Dev	4	5	5	4	4	4	4	5	5	4	4	5
	Min	158	164	158	143	142	160	194	195	190	173	172	189
	Max	175	182	177	158	156	177	211	216	211	188	187	208
Rothamsted	Mean	161	159	163	142	145	163	194	191	196	170	174	189
	St Dev	5	5	5	4	4	5	5	5	5	5	6	6
	Min	150	152	156	130	133	153	185	182	186	160	162	177
	Max	170	169	174	150	153	171	204	200	206	178	183	199
Sutton	Mean	160	163	162	145	144	163	194	196	195	175	174	190
Bonington	St Dev	5	5	5	4	4	5	5	5	5	5	5	6
	Min	148	156	154	135	133	154	183	187	186	165	164	179
	Max	168	173	171	153	152	170	203	206	204	184	183	201
Wallingford	Mean	159	160	160	142	143	161	192	192	193	171	172	187
	St Dev	5	4	5	4	4	5	5	4	5	5	5	6
	Min	149	153	154	132	133	152	183	183	184	160	161	176
	Max	166	168	170	150	151	168	200	200	202	179	180	197
	Mean	164	166	165	148	147	166	199	199	200	178	178	195
	St Dev	5	4	5	4	4	5	5	5	5	5	5	5
	Min	154	158	158	138	137	156	189	190	190	168	167	183
	Max	172	175	175	155	154	174	207	208	209	186	186	204

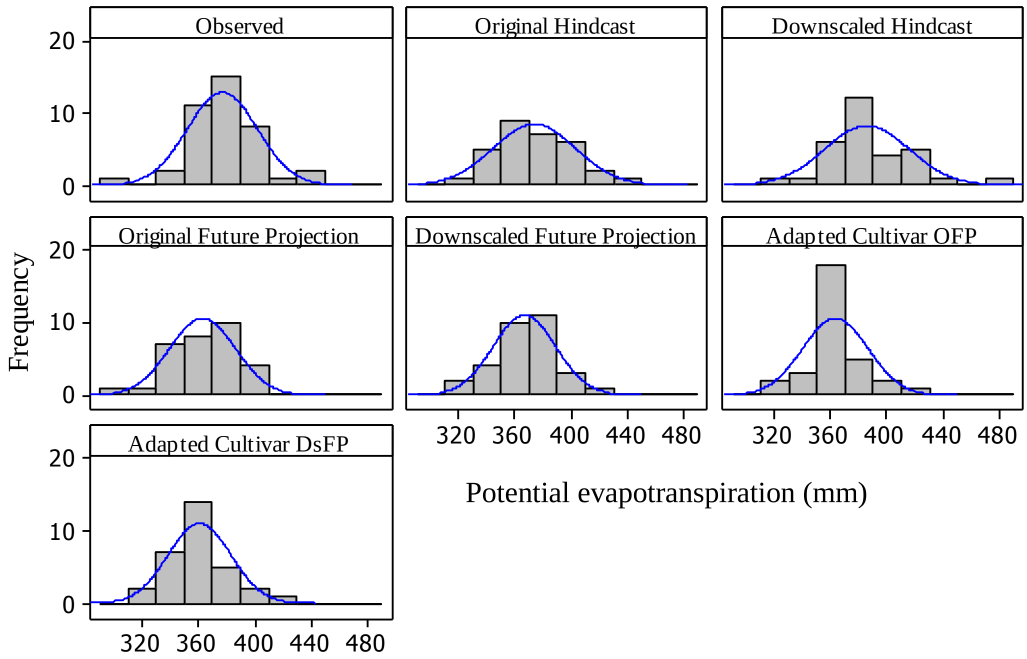


Figure 37. Potential evapotranspiration (mm) estimated by CropSyst for spring barley for all weather data sources at Bush, plus estimates based on potential cultivar adaptations to phenological development using non-downscaled (OFP) and downscaled future projection (DsFP) weather data. NB. Observed n = 40, all others n = 31.

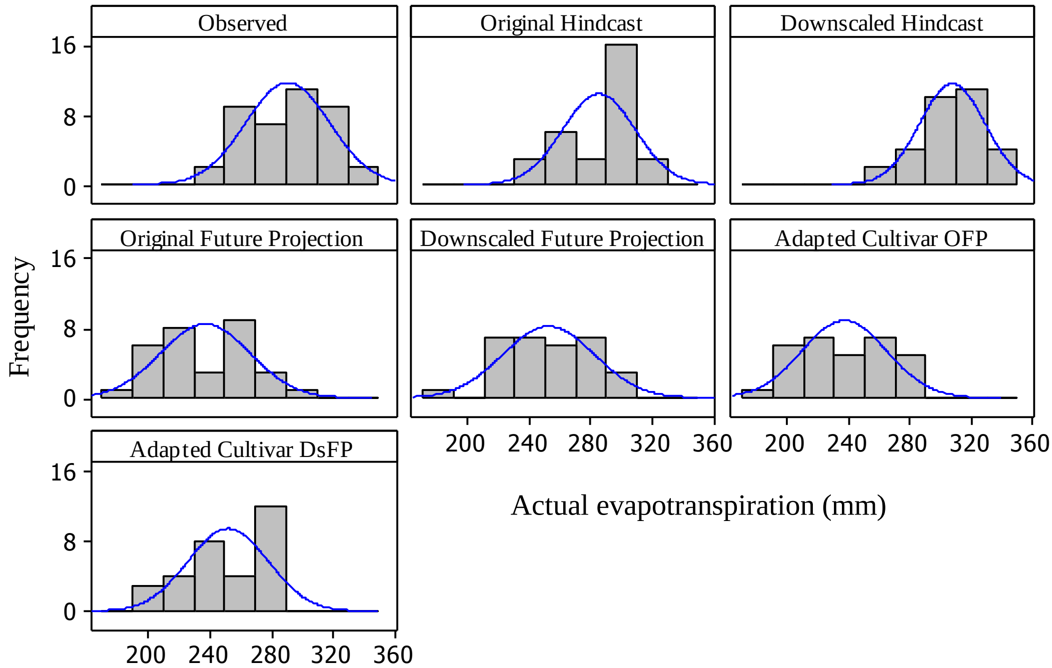


Figure 38. Actual evapotranspiration (mm) estimated by CropSyst for spring barley for all weather data sources at Bush, plus estimates based on potential cultivar adaptations to phenological development using non-downscaled (OFP) and downscaled future projection (DsFP) weather data. NB. Observed n = 40, all others n = 31.

The ratios between potential and actual evapotranspiration change between weather data sources (Figs 37 and 38), but with the AFC DsFP estimates being similar to those from the observed weather data for PotET. However, ActET patterns for all modelled weather data sources are dissimilar from the observed. The AFC DsFP estimates show considerably less ActET than from the observed weather data.

There was a large range in the variability in yield between years, which can partly be attributed to the differences in PotET and ActET, associated plant available soil water, and nitrogen availability. For example at Bush, the lowest yield using observed weather data was 4.186 t/ha in 1979, and the highest yield was 9.797 t/ha in 1999. This can be attributed to a period of nitrogen stress in late April to early May in 1979 and then water stress due to high PotET and low plant available soil water occurring from the end of June (Fig 39 top). Conversely, in 1999, there is no nitrogen stress during early rapid growth, and the plant available water does not decline until the end of July (despite similar PotET), at which time the crop is harvested.

Under the downscaled future climate and with the AFC at Bush, the lowest yield was (6.299 t/ha in the HadRM3 modelled year of 2100, and the highest was 14.182 t/ha in 2095. The highest value is too large given current top yields, but does illustrate potential given favourable growing conditions. In the modelled year of 2100, whilst there was no nitrogen stress, the crop became water stressed from the beginning of June, albeit after leaf expansion had finished (Fig 40). The high yield year was neither nitrogen or water stressed at times when the crop was growing.

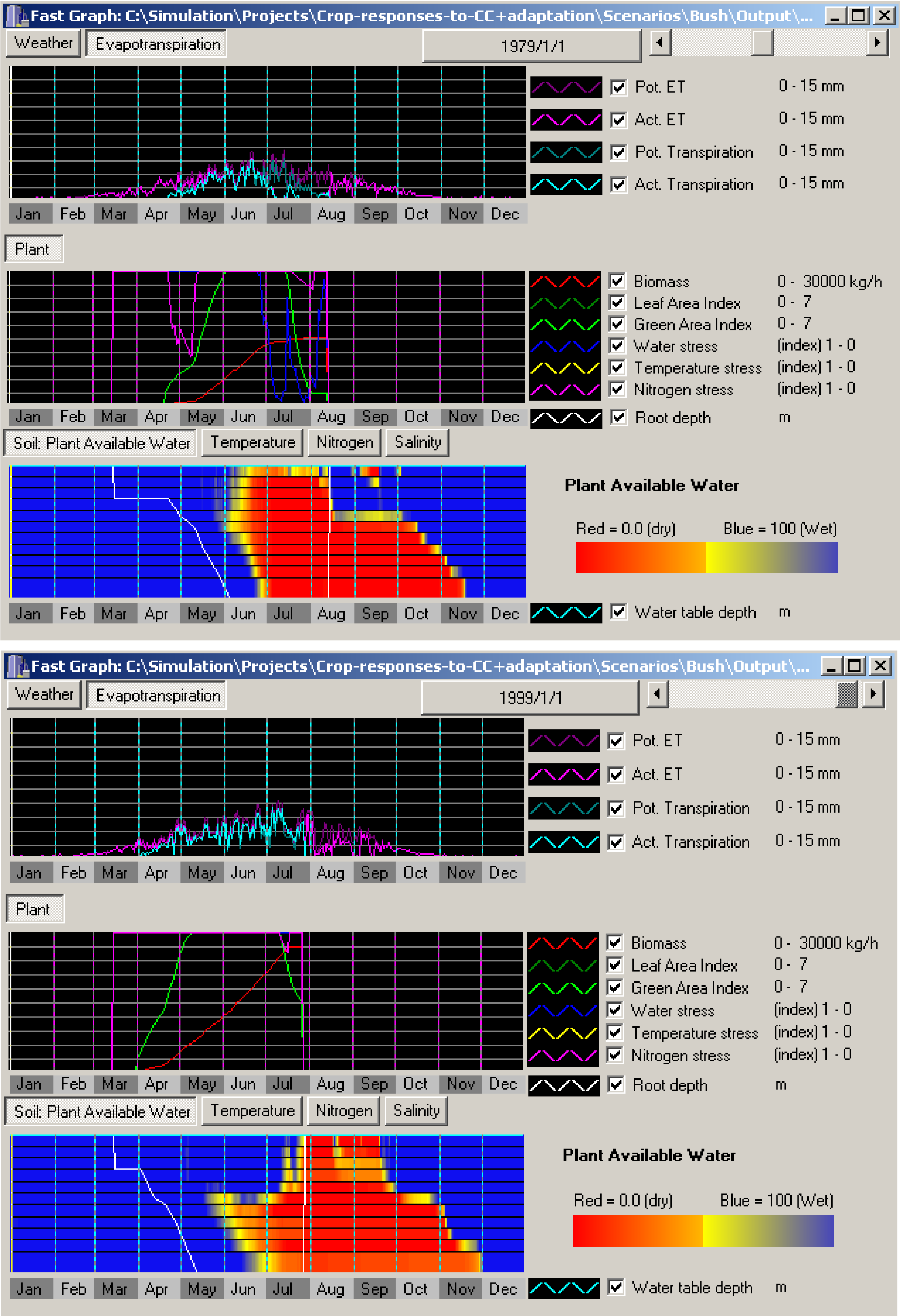


Figure 39. CropSyst estimates of evapotranspiration, plant growth and plant available soil water for the lowest spring barley yield year (4.19 t/ha in 1979, top) and highest yield year (9.80 t/ha in 1999, bottom) at Bush derived from observed weather data.

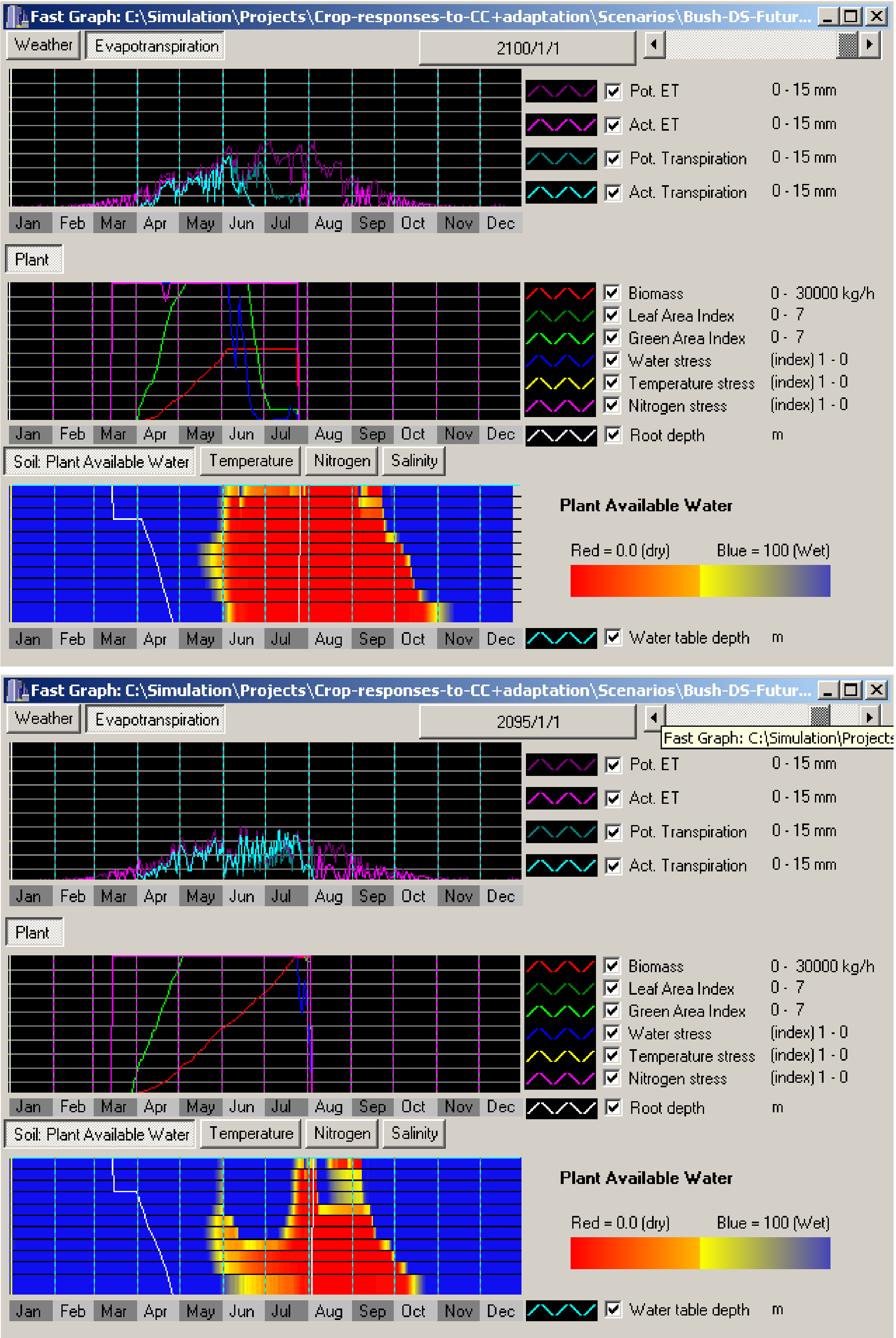


Figure 40. CropSyst estimates of evapotranspiration, plant growth and plant available soil water for the lowest spring barley yield year (6.30 t/ha in 2100, top) and highest yield year (14.18 t/ha in 2095, bottom) at Bush for the adapted future cultivar derived from downscaled future projection weather data.

6.4.2 Spring barley: whole crop harvest.

The whole crop spring barley yields were higher for the AFC with DsFP weather data (Fig 41), whilst achieving similar timings of phenological development (Table 17).

Table 17. Day of year the adapted future cultivar of Spring barley whole crop reaches phenological stages using downscaled future projection weather data compared to those derived from observed weather data at Bush.

Phenological stage	Observed (Day of Year)	Adapted future cultivar (Day of Year)
Emergence	101	92
Begin flowering	173	175
Harvest date	200	199

The adapted cultivar spring barley whole crop was harvested approximately 12 days before physiological maturity (conforming with the current range of 2-3 weeks before harvest for a ripe crop).

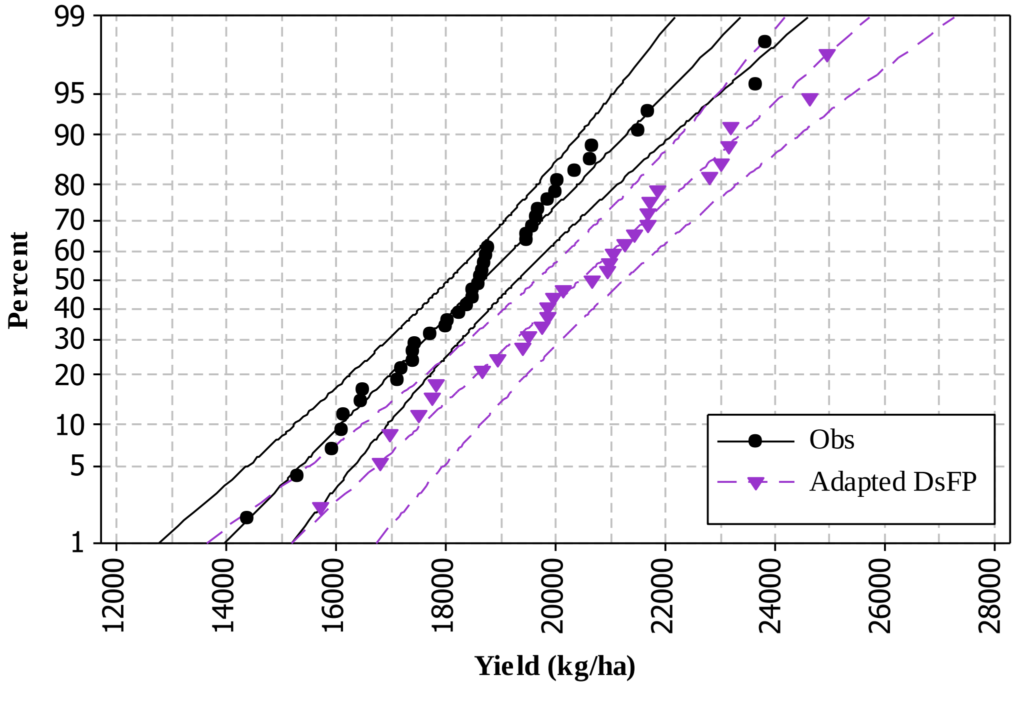


Figure 41. Probability distribution function of estimated total whole crop harvest yields derived from observed and adapted cultivar with downscaled future projection (DsFP) weather data from Bush for a whole crop spring barley simulation.
Note observed n = 40, adapted future cultivar n = 31.

6.4.3 Winter wheat.

6.4.3.1 Evaluation of estimates.

Evaluation of the estimates of winter wheat growth made by CropSyst against the HGCA benchmarks and national level yield values at three sites, indicate that the model was able to reproduce the mean target yield (8.3 t/ha) well (Table 18). However, the variability was larger than that considered within observed variation, particularly at Rothamsted (standard deviation = 2.232 t/ha). The model was able to produce estimates of total root biomass well, but under-estimated initial root growth. The GAI and total dry weight were also under-estimated, despite the early season daily growth rates being similar at Cawood and Rothamsted. Initial calibration efforts had achieved better matches of GAI but had resulted in substantial over-estimations of dry weight biomass and yield. The cumulative canopy nitrogen uptake was under-estimated by 44 kgN/ ha at Bush, but over-estimated by 23 kgN/ ha at Cawood and 13 kgN/ ha at Rothamsted.

Table 18. Evaluation of CropSyst estimates by comparison of modelled versus HGCA Benchmark values for winter wheat growth at Bush (1962-2000, n =39), Cawood (1970-99, n=30) and Rothamsted (1962-99, n=38) representing north, central and southern UK, but parameterised so as to achieve mean yield values of c 8.3 t ha^{-1} (8300 kg/ ha) based on national level statistics.

			Root wt (kg/ha)		GAI		N uptake (kgN/ha)		Total dry wt (kg/ha)		Growth rate (kg/ha/day)		Yield (kg/ha)	
Bush	Date	DoY	Benchmark	Modelled	Benchmark	Modelled	Benchmark	Modelled	Benchmark	Modelled	Benchmark	Modelled	Generic	Modelled
GS30	31-Mar	90	400	105	1.6	1.0								
GS31	10-Apr	100	500	156	2.0	1.4	81	61	1900	853	160	134		
GS39	19-May	139			6.2	4.0	189	165	6900	4959				
GS59	06-Jun	157			6.3	4.9	233	200	11400	8479				
GS61 flowering	11-Jun	162	1000	961	6.3	5.0	248	207	12100	9554	180	186		
GS 71	20-Jun	171			5.7	5.3			13700	11515				
GS87	29-Jul	210			1.3	1.7			19600	18161				
Harvest	09-Aug	221			0	0	282	238	18400	18383			8300	8504
													St Dev	1459
Cawood														
GS30	31-Mar	90	400	162	1.6	1.6								
GS31	10-Apr	100	500	235	2.0	2.1	81	103	1900	1452	160	159		
GS39	19-May	139			6.2	4.6	189	222	6900	7000				
GS59	06-Jun	157			6.3	5.0	233	262	11400	10646				
GS61 flowering	11-Jun	162	1000	990	6.3	5.0	248	270	12100	11733	180	141		
GS 71	20-Jun	171			5.7	4.6			13700	13489				
GS87	29-Jul	210			1.3	0.7			19600	18147				
Harvest	09-Aug	221			0	0	282	305	18400	16157			8300	7661
													St Dev	1774
Rothamsted														
GS30	31-Mar	90	400	196	1.6	1.9								
GS31	10-Apr	100	500	269	2.0	2.5	81	119	1900	1804	160	164		
GS39	19-May	139			6.2	4.8	189	230	6900	7733				
GS59	06-Jun	157			6.3	5.0	233	265	11400	11412				
GS61 flowering	11-Jun	162	1000	986	6.3	4.9	248	270	12100	12446	180	142		
GS 71	20-Jun	171			5.7	4.3			13700	14331				
GS87	29-Jul	210			1.3	0.8			19600	18933				
Harvest	09-Aug	221			0	0	282	295	18400	16794			8300	8439
													St Dev	2232

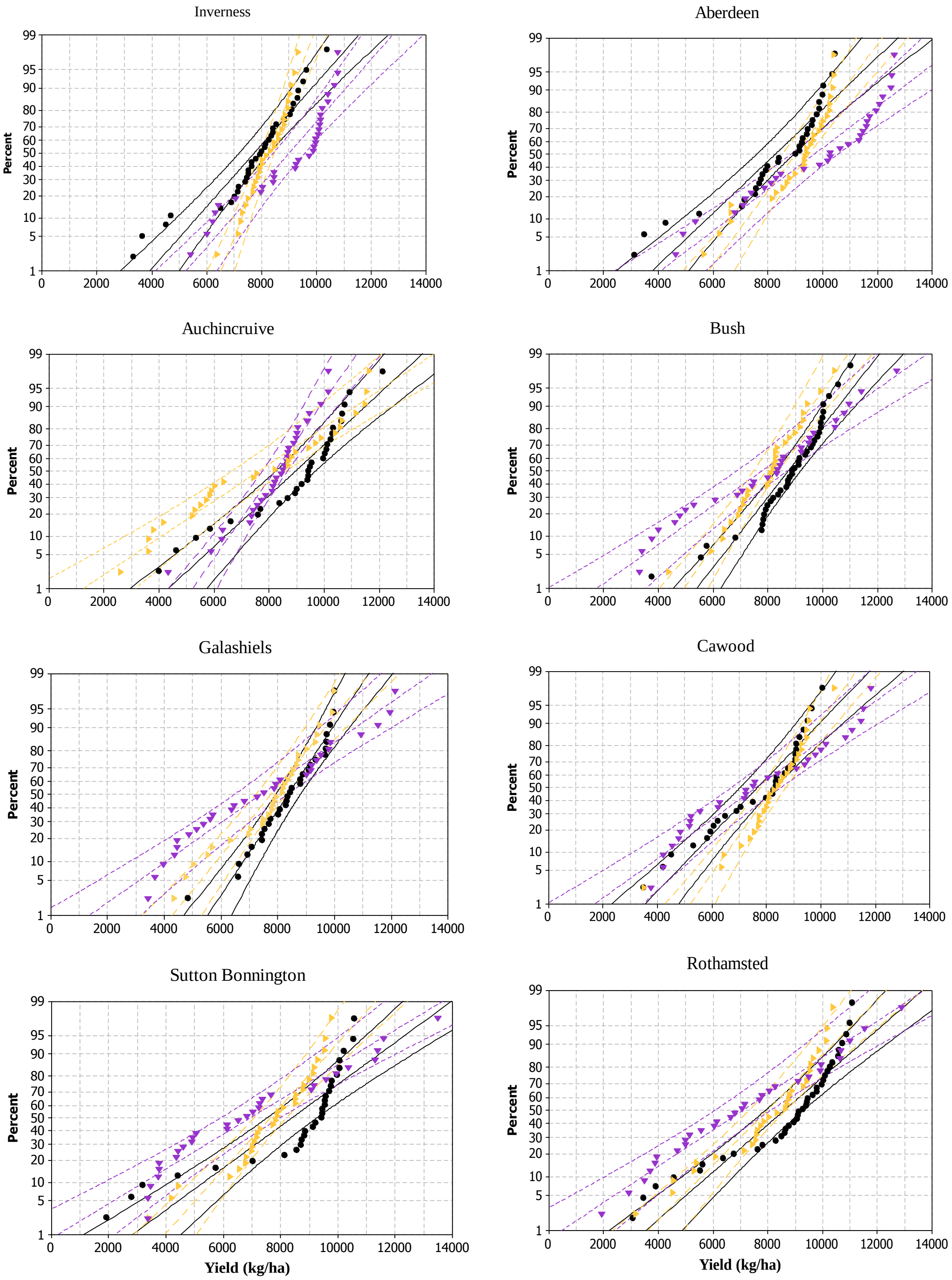


Figure 42. Probability distribution functions of estimated winter wheat yield derived from observed (●) and downscaled future projection (▶) weather data, plus adapted future cultivar estimates (▼) at eight sites in the UK.

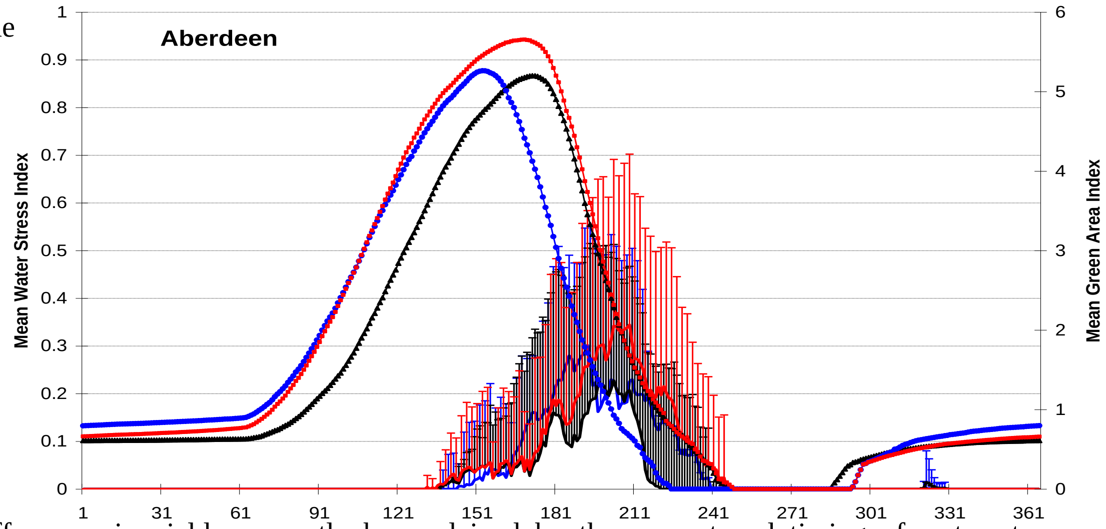
6.4.3.2 Future estimated growth and yield.

For final grain yield estimates (Fig 42 and Table 19), only Inverness and Aberdeen show a clear improvement from using the AFC with the DsFP weather data, with all other sites showing a decrease in mean yields. Without adaptation, these two most northern sites, plus the most southerly (East Malling and Everton, Table 19), show modest increases in yield in the future. At Rothamsted and Sutton Bonington neither future sets of estimates improve on those from the observed weather data. Generally there is a pattern seen that sites in the south of the UK have a decrease in yield in the future and increased variability, either with or without phenology based adaptation. There is less variability seen in the future projection without adaptation, but variability increases with the AFC above that modelled using the observed weather data.

Table 19. Mean winter wheat yields from observed and downscaled future projection with and without phenology based adaptation. Differences are estimated – observed.

	Winter Wheat Yield (t/ha)							
	Observed		Downscaled future projection (no adaptation)			Downscaled future projection (with adaptation)		
	Mean	St Dev	Mean	Diff	St Dev	Mean	Diff	St Dev
Inverness	7.733	1.632	8.087	3.54	0.722	9.006	1.27	1.612
Aberdeen	8.260	1.926	9.002	0.74	1.361	9.686	1.43	2.413
Mylnefield	8.573	2.020	8.087	-0.48	1.669	7.689	-0.88	2.820
Auchincruive	8.948	1.981	8.198	-0.75	1.284	7.606	-1.34	2.736
Bush	8.737	1.431	7.927	-0.81	1.291	7.770	-0.97	2.591
Galashiels	8.360	1.220	7.753	-0.61	1.496	7.393	-0.97	2.596
Cawood	7.661	1.774	8.240	0.58	1.312	7.606	-0.55	2.545
Sutton Bonington	8.381	2.394	7.627	-0.75	1.583	6.922	-1.46	2.886
Rothamsted	8.591	2.176	7.972	-0.62	1.874	7.067	-1.52	2.845
Wallingford	7.812	2.232	7.590	-0.22	1.588	6.307	-1.50	2.652
East Malling	8.155	2.412	8.237	0.82	1.527	8.108	-0.47	2.397
Everton	8.596	2.626	8.664	0.68	1.742	7.776	-0.82	2.880
Mean	8.317	1.985	8.115	-0.20	1.454	7.745	-0.57	2.581

The



differences in yield can partly be explained by the amount and timing of water stress experienced by the crop at each site. Under good growing conditions, the crop would not experience water stress whilst the leaves are still green and photosynthesising, but dry conditions would occur as the crop reaches physiological maturity and at harvest.

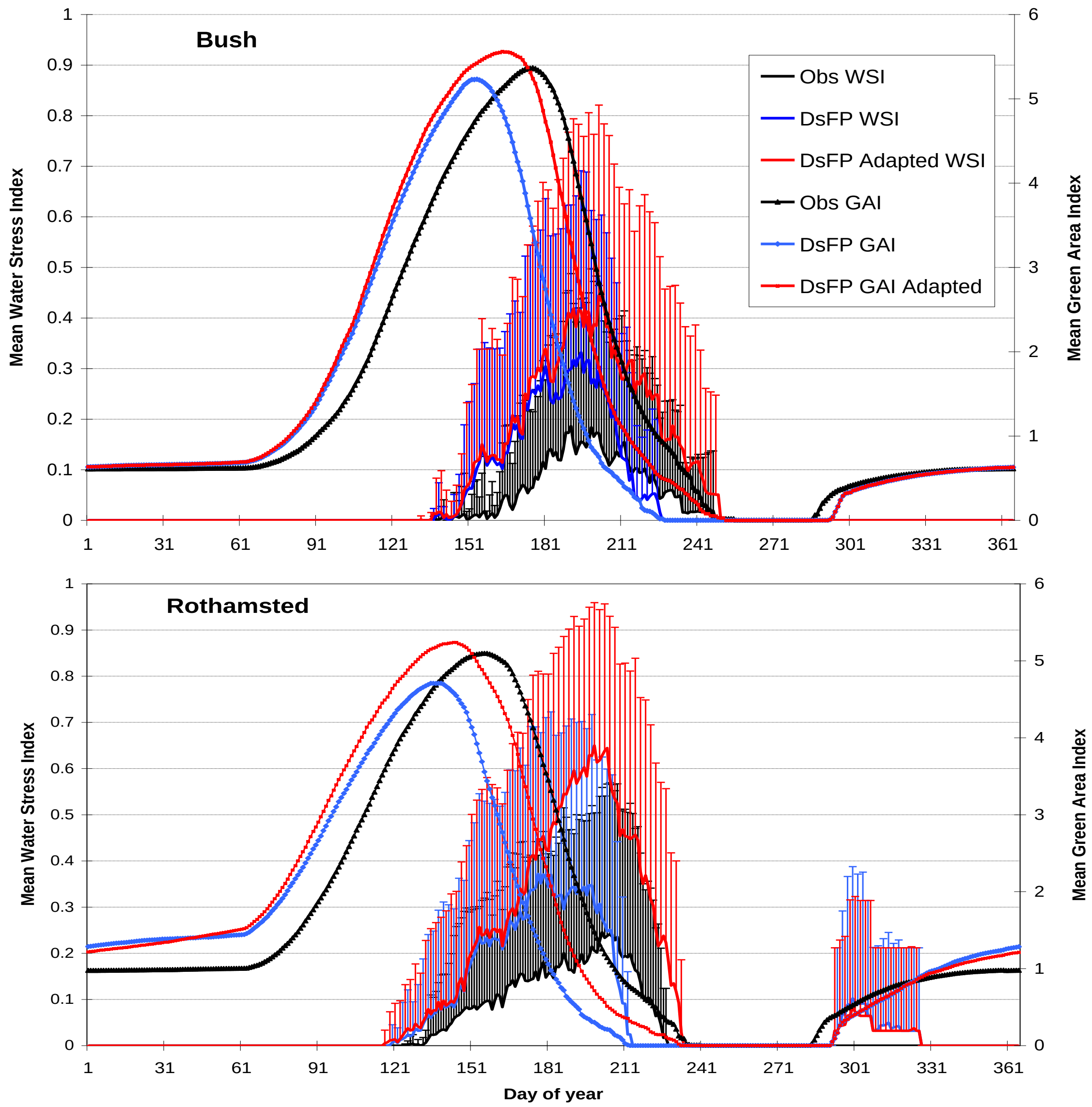


Figure 43. Mean Water Stress Index (lines and bars) and mean Green Area Index (points and lines) at Aberdeen, Bush and Rothamsted from observed (black) and downscaled future projection (DsFP) (blue) weather data, plus DsFP adapted future cultivar (red). Bars are calculated standard deviations above the mean Water Stress Index.

Figure 43 shows that at Aberdeen, for observed and future conditions, little water stress occurs as the crop reaches full canopy cover, but drier conditions exist as the crop dries and material is translocated from leaves and stems to grains. At Bush, and more so at Rothamsted, the crop experiences higher levels of water stress under the future scenario, a problem accentuated by the adaptation to phenological development, which places the later stages of crop growth into an increasingly water stress period. Also at Rothamsted under the future weather, water stress is estimated to increase in the autumn as the newly emerging crop becomes established, whereas with the observed weather data, no water stressed occurred. Despite this, the Rothamsted crop achieves a higher GAI over the winter under the future weather scenario. Although the winter wheat crop parameterisation contained constraints to restrict growth over the winter period (based on temperature and duration of cold periods), the Rothamsted crop expands the GAI in January and February, giving a larger canopy leaf area at the onset of spring (c. day 70 to 80), but at a time when physical damage by frosts and wind can still occur, and access limitations due to wet soils exist (Chapter 5).

6.5 Discussion.

6.5.1 Model estimate utility.

The utility of the estimates made by CropSyst for both spring barley and winter wheat and how they are interpreted is to a large extent a function of a combination of factors: the quality and coverage of calibration data; the level of parameterisation effort; model user skill; and post simulation evaluation effort. The results presented here are based on limited calibration data for crop growth (and non-existent for below ground processes), restricting options for more comprehensive statistical testing. Correspondingly the evaluation effort has been limited, particularly in respect of components of the CropSyst model for which there was no calibration data (i.e. soil water and nitrogen). Such issues of model validation and estimate utility are further complicated for cases where simulations are made under future climatic conditions (Bellocchi *et al.* 2009). Whilst CropSyst may have been able to reproduce estimates (using observed weather data) that were close to means (i.e. yield) and benchmark values, the variability must be considered as too large. Also, the estimates made for future projections will have a lower variability than those based on observed weather data. This is due to the HadRM3 producing weather data estimates that are targeted at achieving mean climatic conditions, rather than capturing the observed variability in the weather (Chapter 3). However, the results gained for both crops using the observed weather data conform to overall expectations of growth and development. Where individual yearly results are at the extreme end of the variability, the indications were that that the model was overly sensitive to the impacts of nitrogen and water stress. As such the results gained for future climatic conditions provide a useful indication to potential responses by the two crops, giving a generic impression of the impacts, but interpretation of specific aspects of the results does require consideration of the limits to the estimates' utility.

6.5.2 Impacts on Spring Barley.

Using a cultivar adapted for slower phenological development could utilise the benefits of the future climate scenario, by maintaining the length of time the crop has to accumulate biomass during favourable conditions whilst avoiding the negative impacts of water stress. Without such adaptations the crop matures more rapidly due to higher temperatures giving a faster thermal time accumulation rate, thus the crop reaches physiological maturity earlier, giving a shorter time for biomass accumulation. This appears to be consistent across all sites within the UK, but the benefits are seen more clearly in northern areas.

Critical to the level of risk of having a low yield is the timing at which either nitrogen of water stress occurs. Whilst nitrogen stress can be alleviated through management, the crop is more prone to water stress if soil plant available water becomes limiting whilst the crop is still photosynthesising. This study has not considered an alternative adaptation option of an earlier sowing date, partially due to the evidence in Chapter 5 that soils may still be at or above field capacity at the time of sowing, even though growing conditions may be favourable. However, an earlier sowing date would improve the probability of avoiding water stress conditions in the summer.

Evidence from the CropSyst estimates (and the agro-meteorological metrics) also suggests that the higher soil moisture deficits and later recharge after the spring barley harvest may pose restrictions on establishment of the nest crop within the rotation. An earlier planting date would increase the period within which a newly planted crop is exposed to water stress at emergence or increase the length of the fallow period.

The risk of an overall decrease in spring barley yield in the future appears low, with only sites in southern UK showing reduced yields in years when water stress is higher and earlier in the year. With respect to the use of spring barley for livestock feed, the evidence from the whole crop simulations indicate that more biomass would be available, but the estimates do not permit indications as to the effect on dry matter content and feed quality. However, the increase in available whole crop biomass at the start of periods when water stress is high may be more significant in the future, when grass grazing availability may be expected to be restricted due to the water stress.

6.5.3 Impacts on winter wheat.

For winter wheat, the phenology based adaptations appear to be counter productive, as they extend the period when the crop is still photosynthesising into times when soil plant available water is limited. Under the future scenario, the non-adapted (original) crop performs better than the adapted one at most sites tested. The exceptions were Inverness and Aberdeen, which also showed the most favourable response for spring barley. The benefits of the adaptations appear to decrease and become negative the further south the site is in the UK.

There is a potential increased risk of nitrogen stress in spring and summer due to higher rates of mineralization over the winter in the future. In some projected years, CropSyst estimated crop growth during the winter, despite imposed temperature based growth parameter restrictions over the winter (but with a base temperature of 0°C for thermal time accumulation), and albeit at a slow growth rate. However, this implies some nitrogen uptake when soil nitrogen levels are low, potentially requiring higher nitrogen inputs from management in the spring. The rate of growth in the autumn may be excessive in the future, and beyond the control of plant growth regulator applications, potentially giving crop canopies that are too large over the winter and therefore more vulnerable to physical damage (from wind, snow compaction and frost). A later planting date may result in smaller over-winter canopy size, but exposes the risk of poor weather for seedbed preparation and sowing. Given that winter wheat is grown at much lower latitudes (i.e. Spain, North Africa and the Middle-East), it is unlikely that the warmer conditions projected for Scotland over the winter pose a threat to the process of crop vernalisation for winter crops, on the basis that there are still sufficient colds periods in the future climate projections (i.e. see Figure 11). A more relevant risk is associated with the timing of heat stress relative to the phenological stage (i.e. Wheeler *et al.* 1996), particularly at anthesis (Woollenweber 2003).

6.5.4 Further Issues.

The estimates gained from CropSyst do not take into consideration the impacts on weeds, pests and pathogens on cereal production. Whilst the indications for the scenario used are that crop growth may improve in the future, it would be reasonable to assume that the same will apply to weeds. However, the distribution and impacts of pests, weeds and diseases on crop yields are only slowly starting to be quantified in modelling structures (Gregory *et al.* 2009). Pathogen survival may increase over milder winters, and warmer summers with higher relative humidity increases dispersal, giving greater risk of crop infestation. Therefore additional management (herbicides and pesticides applications, mechanical weed control etc.) may be required. The policy driven requirement for management to optimise carbon capture and minimise GHG emissions may also become more prescriptive in how crops are managed. A further cultivar option may be a return to longer stemmed varieties that have the advantage of capturing more carbon, but are also more vulnerable to lodging.

This potential increase in economic viability may have consequences for land use decision making regarding choices between cereals and grassland in currently marginal cereal areas (i.e. Land Capability for Agriculture class 4), with consequences on soil carbon storage. A reduction in climatic constraints may result in an expansion of cereal area cultivation and ploughing up of grassland, risking an increase in GHG emissions and reduced carbon capture.

6.6 Conclusions.

The results indicate that spring barley and winter wheat may remain viable and competitive land uses in Scotland, with relatively little change to the way the crop is managed. What management changes may be required centre around the timing of operations (i.e. sowing and harvest) and the need for adaptive responses to soil water and nitrogen conditions. The potential increase in productivity in Scotland (particularly the more northern sites) under the future climate scenario, when compared with production levels in southern UK (and the potential for yield reductions in overseas locations where water availability limits growth), indicates that cereals will remain an economically viable product. This however depends on the impacts of climate change on cereal production on a global scale. Elsewhere in the UK increases in spring barley yield also appear to be a possibility, but with an increase in risk potential due to higher levels of water stress. Whilst winter wheat growth will still be possible across the UK, Scotland may gain a competitive edge due to increased yields and lower levels of risk.

A limitation of this work however, is that a single ‘generic’ soil type was used at all the different sites, hence errors could have been introduced and the actual crop and soil responses be different. The results presented are indicative but not soil specific. Further research should utilise a range of soil types per location to explore the range of responses driven by soil type. Also, this study has not examined the impacts of weather events at the time of harvest, or the combination of soil wetness, growth stage and wind conditions that would cause lodging.

Chapter 7: Grass Systems Modelling.

7.1 Abstract.

This Chapter investigates the utility of estimates made by the CropSyst model in representing grass systems. Though there are many grass models available, CropSyst was chosen as it has a generic framework, permitting representation of a wide range of other land uses, and has a structure that permits alterations and additions of functions whilst retaining its core modelling processes. A set of *a priori* evaluation criteria were set to determine whether the model achieved a sufficient quality of estimates. Estimates made by the model were initially compared against observed yield data from the Scottish Agricultural College's commercial grass trials data. A simulation was also constructed for observed silage yields from a farm in south west Scotland. Further to this evaluation, a set of simulations were conducted to represent three grass systems: un-managed; a one cut silage; and an artificial grazing regime. These simulations were run using observed and downscaled future projection weather data. The results of the trials simulation evaluations showed that the model did not meet the *a priori* criteria of estimate quality. The model did produce estimates that broadly fitted the pattern of yield response, but had large estimate errors. For the three productions systems, the model was able to achieve results that were stable and had estimates with credible magnitudes, but when run using the future climate scenario data, the estimates showed large errors and unstable patterns. The failure of the model to meet the *a priori* evaluation criteria meant that the estimates should not be used in any further levels of investigation.

7.2 Introduction.

Grass production in Scotland underpins all the livestock production systems, with cultivated grass accounting for approximately 1.3 m ha in Scotland (see Table 14, Ch 6). Changes on a global scale (economics and policies, population and dietary choices, GHG reduction measures, as well as climate change impacts) may ultimately determine availability and demand for cereal and livestock products. However, it is necessary to investigate how a site's grass production capacity changes and what the impacts on livestock production is, or whether alternative land uses become preferable.

To do this, the CropSyst model was adapted so as to include grass as a modelled crop, with additional management parameters to facilitate silage harvesting and grazing off-take within the simulation. This was done in collaboration with the developers at Washington State University. Evaluation of the modelling of grass is demonstrated against observed yield data from a series of grass variety trials at three sites in Scotland (Auchincruive, Bush and Aberdeen). The aim was, upon satisfactory evaluation of CropSyst grass modelling capabilities, to use the model with downscaled future climate projection data to estimate changes in grass production. The extent to which the range of grass productions systems would be represented, level of detail of analysis and utility of the estimates to draw conclusions on the impacts of a changed climate would depend on the results of the initial evaluation. A set of *a priori* evaluation criteria were set that the model had to satisfy before detailed analyses would be conducted. The proviso was set that *if* the model was able to satisfy the evaluation criteria, then estimates made by CropSyst of future grass production would be integrated with the livestock sub-model within the whole farm model (LADSS). However, *if* the evaluation criteria were not met, then the CropSyst estimates of future grass production would not be used within the whole farm model. As the response of grass systems to an changed climate is essential to the potential dynamics of management and the land use mixes within a farm, failure to meet the evaluation criteria would effectively prevent the whole farm modelling simulations being conducted.

7.3 Materials and Methods.

In collaboration with the CropSyst developers at Washington State University, model structures and parameter functions were developed in order to enable the representation of a perennial ryegrass crop. My contribution to this consisted primarily of six main additions:

- Setting specifications for new modelling functions that utilised existing modelling capabilities.
- Establishing mechanisms for controlling the amount of removal of biomass by grazing animals and / or machinery. Specifically this meant setting the specifications for new parameters that permitted flexible representation of off-take by a range of grazing animals (i.e. type of off-take in respect of balance of live and senesced material).
- Ensuring grass sward viability through specifying the type of removal (fixed amount of based on a percentage of total biomass) and control for maintaining minimal amounts of green area index, and controlling the amount of biomass that could be removed and keeping a reserve amount of biomass and leaf area index to enable re-growth after off-take (this was based on the WSU team not being able to develop a process for translocation of resources from root material).
- Developing the way that senesced material is represented and handled in terms of material entering into residue pools within the soil and hence influence on organic matter content and nutrient cycling.
- Altering the leaf area index responses and leaf longevity in relation to biomass off-take by animals or machinery.
- Scheduling controls for setting when management events occur.

These developments were iterative, based on estimate responses to calibration and testing. However, a constraint placed on the development by the WSU team was that the core modelling components (used to estimate other crops within the CropSyst capabilities) had to remain, hence changes to facilitate grass representation could not affect the way other crops were represented. A limitation of the process of adaptation of CropSyst was that the WSU team could not undertake alterations to the way the model represents the balance between above ground and below ground biomass accumulation. Rather than developing functions that enabled representation of translocation of material between roots and leaves, the WSU team preferred the approach of ensuring that there was a minimum amount of green area index (GAI). This was because of the need to utilise a key equation within the model where daily growth is calculated using a value for the GAI from the previous day. Effectively this meant that the root biomass reaches a maximum and then stays stable, not reflecting seasonal changes or responses to above ground biomass off-take. These developments took place over a period of several years and was done on the basis that changes and developments would be done secondary to the CropSyst team's other workload.

7.3.1 Calibration.

The Scottish Agricultural College (SAC) conducts grass variety trials at three sites in Scotland (Auchincruive, Bush and Craibstone, near Aberdeen) according to a prescribed management regime (DEFRA 1998), so as to determine the relative performance of varieties compared against a benchmark perennial ryegrass cultivar (commercial name of Condesa). Access was gained to the Condesa trials data for the period 1994 to 2003. In some cases data were available for two trials at the same site sown in the same year, but these trials could not be considered as a replicate, due to differences in soils and management. The trials provided suitable information with which to create CropSyst simulations representing the trials' conditions and observed yield data to compare against modelled estimates, but lacked data on observations of soil moisture and nitrogen. Soils data were provided either from site surveys or by the grass trials managers. Fertiliser application amounts and dates were recorded as part of the trial, as were dates of cuts and associated yield. Weather data were from meteorological stations at the trials sites.

The trials lasted four years:

- Sowing year:
  - Seed rate at 22 kg/ha sown between May and August.
  - Plots cut at the discretion of the trials manager to establish a 'dense uniform sward'.
  - Nitrogen applied at discretion of trial manager, in line with official advisory publications.
- Year 1: 'Conservation management'.
  - 4 cuts per year (occasionally 5) at a height of 6 cm, generally at 6 week intervals.
  - Nitrogen applied 9 weeks before first cut (60 - 100 kg/ha), after first cut (90 kg/ha), after second cut (90 kg/ha), after fourth cut (35 kg/ha)
- Year 2: 'Simulated grazing management'.
  - 7 – 10 mechanical cuts per year at a height of 3 cm at set dates (± 3 days) starting on 20th March
  - Nitrogen applied February / March (50-80 kg/ha) then after each cut (35 kg/ha)
- Year 3: 'Conservation management'.
  - 4 – 5 cuts at a height of 6 cm generally at 6 week intervals.
  - Nitrogen applied 9 weeks prior to estimated date of first cut (100 – 125 kg/ha), after first cut (90 kg/ha), after second cut (90 kg/ha) and after all further cuts (35 kg/ha).

CropSyst simulations were created to represent continuously the whole four year period of a trial. Parameters were set to replicate the management regime during years 1-3, with cutting events being set to the observed dates and then fertiliser events related to these dates. In the simulated sowing year, using the clipping management functions within CropSyst, parameters were set so that the grass was managed to represent a dense uniform sward, with a Green Area Index (GAI) between 1 and 2, with an approximate over-winter above ground biomass (AGB) of 2500 kg/ha. For all trials and sites, cutting events were set so that a minimum amount of biomass remained (2500 kg/ha), with a minimum retained GAI of 1. In this way, each site had it own unique set of simulations, varying by management (date of cutting and fertiliser amounts) with site specific soils and weather data, but with the same crop parameters.

An independent data set of yields from four fields at the SAC Crichton Farm (near Dumfries) in 2007 for a three-cut silage system was also available for evaluation purposes. A simulation was created using crop parameters from the grass trials calibration, weather and management data from the farm. Soil parameters were the same as for the grass trials as no field specific data were available. The simulation was aimed at representing the mean yields across the four fields for the first, second and third silage harvests.

7.3.2 Construction of grass production systems simulations.

Here the aim was to utilise the grass crop parameters determined from the SAC grass trials calibration and evaluation work within simulations of three generic grass management systems:

- Unmanaged (no fertilisers, cutting or grazing):
    - Initialised such that water and nitrogen were not limiting factors at the start of the simulation.
    - No cutting or grazing management interventions.

    - The purpose was to investigate whether the model could achieve a stable continuous multiple year flow of seasonal growth and senescence.
- Silage conservation:
    - Continuous simulation from 1961 (sowing year) to 2000 with observed weather data, and year to year carry-over effects (no recalibration of soil water or nitrogen values). Plus the same with DsFP weather data for the future period ‘2070-2100’.
    - Single silage cut made on 3rd July each year, based on 90% removal and 10% remaining as live standing material.
    - 200 kgN/ha as nitrate (NO_3) and 50 kgN/ha as ammonium (NH_4) applied on 15th March, plus 150 kgN/ha in the form of organic manure applied on the 1st March each year.
- Artificial representation of livestock grazing:
    - 100 kg/ha/day off-take by animals only when the total above ground biomass was above a minimum of 3000 kg/ha starting from the 1st April and ending on the 31st October each year.
    - A minimum GAI of 1 was forced on days when off-take was possible.
    - No fertiliser events were scheduled, instead the CropSyst function of nitrogen being automatically applied to plant material was used.

Simulations of these three systems were created within CropSyst and run using soils data and observed (1961 – 2000) and downscaled future projected weather data from the place of application.

7.3.3 Grass simulation evaluation criteria.

The essence of model validation consists in defining criteria that will be taken into consideration in the choice of an “acceptable” model, and then testing the model performance according to those criteria (Bellocchi *et al.* 2009). The aim of evaluating the CropSyst model's ability to represent grass systems was not to conduct a detailed validation exercise, but to test performance of several key estimates against a set of pre-set criteria in order to decide whether the estimates had sufficient utility for use in further modelling at the whole-farm scale. Prior to commencement of the calibration and evaluation process, a number of *a priori* non-statistical based criteria were set by which to assess the model performance:

1. Simulation of the mean yields per cut at each of the three SAC grass trials sites must be within +/- 10% of the observed mean yield.
    a. With physiological values that conform to perceived ranges or values cited in the literature (i.e. leaf area index).
2. Simulation of each SAC trial must have estimated individual yields per cut within +/- 15% of each single observed yield.
3. Individual trials simulations of specific variables: above ground biomass (AGB); leaf Green Area Index (GAI); and live green biomass (LGB), must achieve a stable series of estimate patterns in relation to known patterns (no single estimate > 50% of the mean, or series of estimates over time that differ substantially from either each simulation or the observed) over the time period of the simulation.
4. Simulations of continuous un-managed grass must achieve stability of yearly estimates of growth and senescence for the full duration of the simulation (i.e. maintaining seasonal variation without overall accumulation of above ground biomass).
    a. With crop physiological values that conform to observations or values cited in the literature (i.e. leaf area index).
    b. With estimates of soil processes (water, nitrogen, organic matter content and mineralisation) that conform to observations, values cited in the literature or are deemed acceptable by expert review.

5. Simulations of the one cut silage conservation system must achieve stability of yearly estimates of growth and senescence for the full duration of the simulation, and produce silage yield estimates within +/- 10% of generic national level yield values relative to amount of nitrogen fertiliser added (i.e. SAC 2009).
6. Simulation of grazed systems must achieve stability of yearly growth and response to continuous off-take during the period when growth would be expected to occur.
    a. Simulations must be able to support a given number of livestock per hectare for a set amount of daily off-take requirements per animal.
    b. With crop physiological values that conform to observations or values cited in the literature (i.e. leaf area index).
    c. With estimates of soil processes (water, nitrogen, organic matter content and mineralisation) that conform to observations, values cited in the literature or are deemed acceptable by expert review.

Graphical based visual techniques are an accepted initial step for model estimate evaluation (i.e. Bellocchi *et al.* 2009), hence the CropSyst representation of the SAC grass trials were first evaluated by:

- Plots of mean yields (all trials per site) showing 10% error bars.
- Plots of individual trials' observed versus modelled estimates comparisons showing +/- 15% tolerance range.

No *a priori* criteria were set for achievement of statistical testing between observed and modelled estimates, on the basis that insufficient site specific combined observations (i.e. physiological measurements, yields, management, soils and weather data) were available. *If* the model conformed with criteria 1 and 2, statistical tests would be conducted to provide more detailed evaluation of model performance. The ability of the model to meet criteria 1 and 2 would determine whether CropSyst could be used to make estimates of grass systems production, and therefore the grass – livestock relationships and dependencies within the whole-farm model.

7.4 Results.

7.4.1 Grass trials evaluation at Auchincruive.

The estimates of yield in the SAC grass trials simulations made by CropSyst failed to meet the evaluation criteria 1 and 2. At all three sites, the means of some cuts where within the +/- 10% range (e.g. at Auchincruive year 1 cuts 1 and 3, plus year 3 cut 4, see Fig. 44). The majority of mean cuts (13 out of 18) were however outside of the criteria 1 range.

The model was partially able to represent the pattern of mean yields in year 1 at Auchincruive, but growth was too great in years 2 (cuts 2-7) and 3 (cuts 1-3). The individual cut estimates show a wide range of ability to meet criteria 2 (individual estimates per cut to be within +/- 15% of observed value) (Fig. 45).

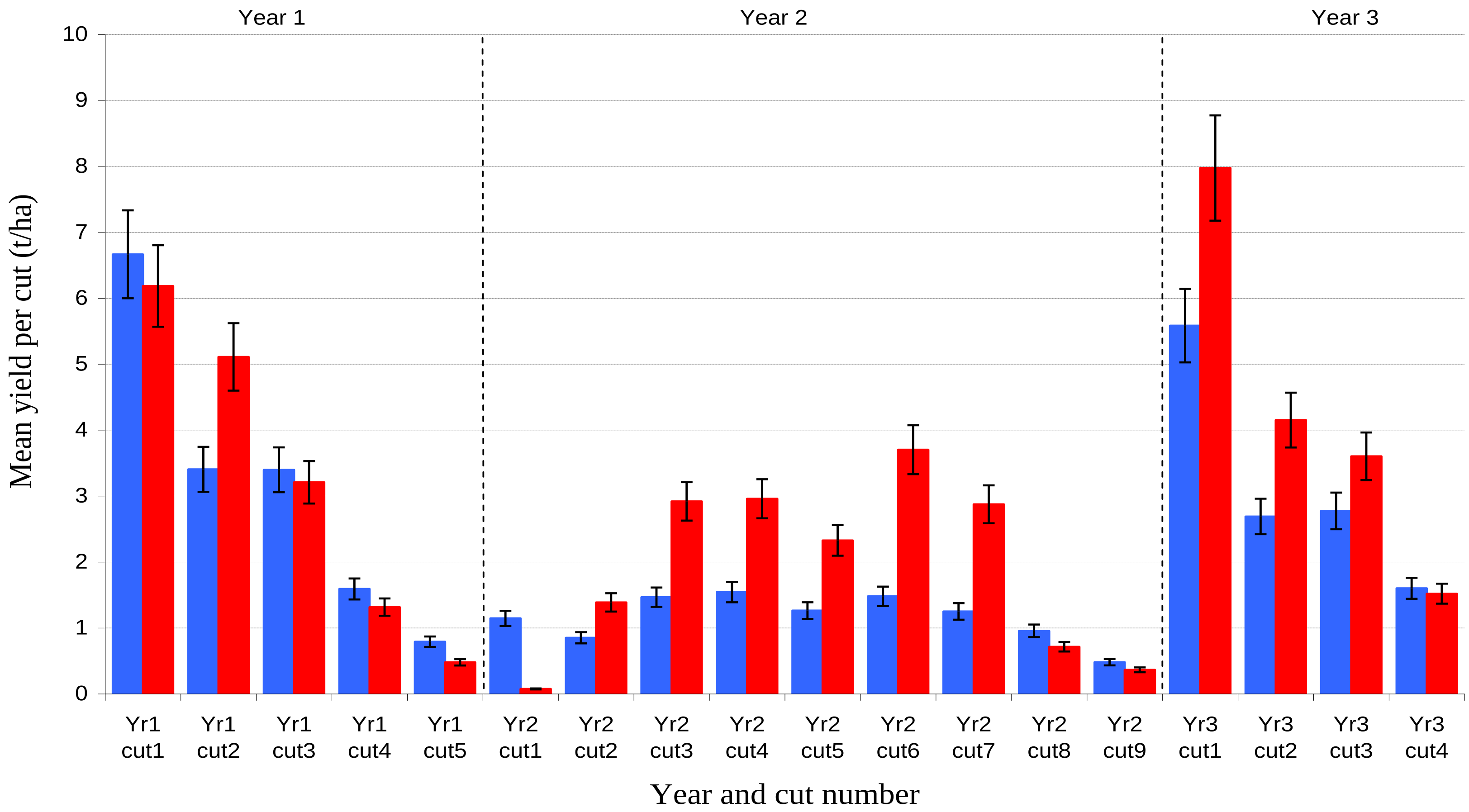


Figure 44. Observed (blue) mean yields per cut from the Scottish Agricultural College grass trials at Auchincruive compared with CropSyst mean modelled (red) estimates derived using observed weather data. Bars show +/- 10% of the mean value.

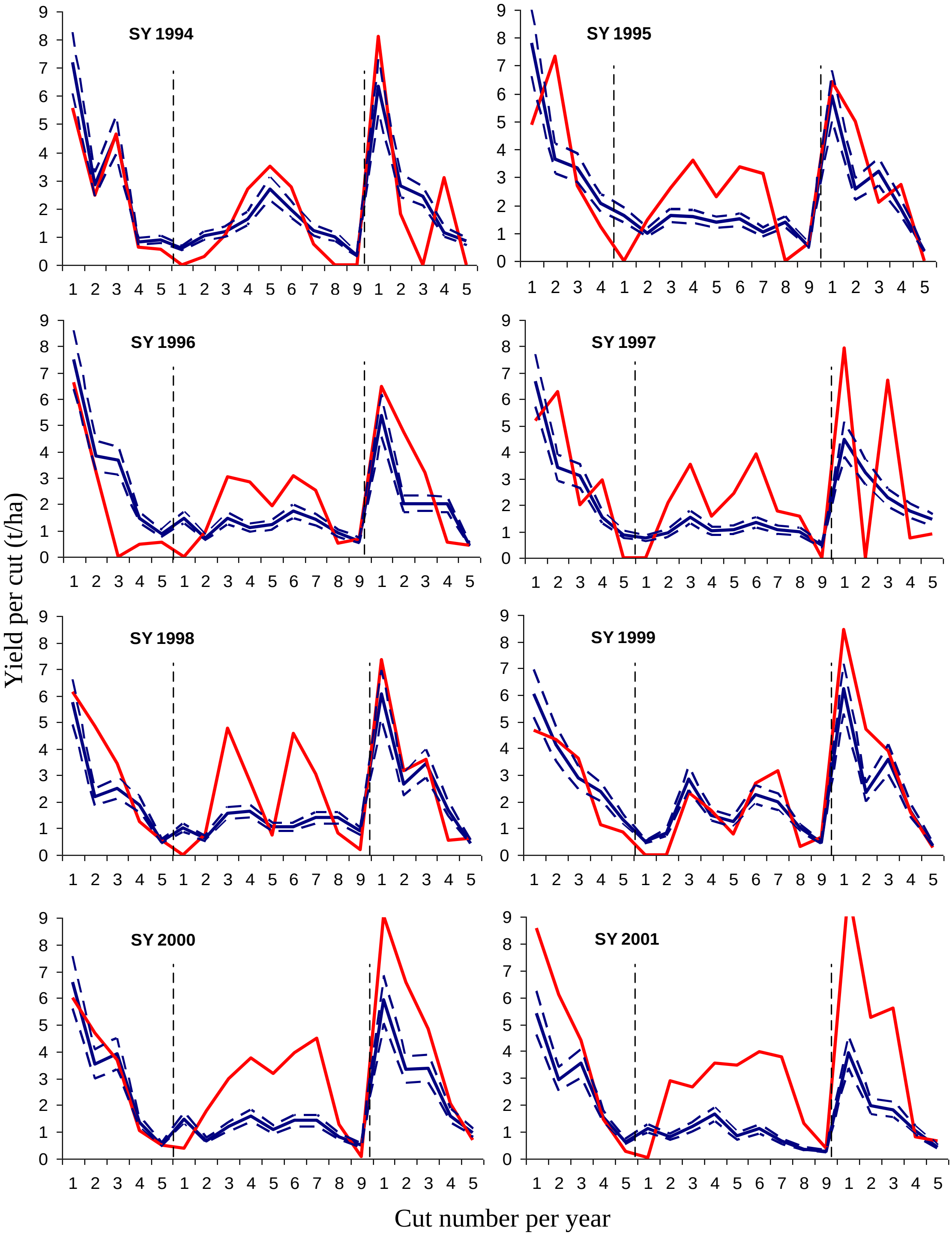


Figure 45. Observed (solid blue) with +/- 15% range (blue dashed) and estimated (red) yields per cut and year for each individual trial at Auchincruive.
(SY = sowing year, vertical dashed lines separate years 1, 2 and 3).

The model failed to meet criteria 2 at all three sites, though some individual estimates per trial were within the +/- 15% range. At Auchincruive the model was able to represent the pattern of yields well in sowing year 1999 (Fig. 45), but with over- and under-estimates per cut > +/- 15%, whilst for other trials both the pattern and quantities show large errors, i.e. sowing year 2001.

There was an inconsistency in the estimates in terms of the response of the crop to a cutting impact and the effect on the subsequent size of cut. For example, the trial starting in sowing year 1997, year 3 cut 2 is 0. Here the observed year 3 cut 1 yield was 4.485 t/ha, the estimated cut was 7.95 t/ha, however for the next cut the observed was 3.223 t/ha, but the estimate was 0 (due to insufficient biomass to permit the cut and retain the minimum AGB). The following cut 3 was estimated at 6.724 t/ha, whereas the observed yield was 2.263 t/ha. Such a pattern is seen in sowing year1994, but not the other trial years.

Variation in the yield amounts are partially explained by differences between trials in the AGB, GAI and LGB. However, in the absence of observed values for these variables it was not possible to make direct comparisons. Figure 46 shows that there was a large variation about the mean for AGB, GAI and LGB. In the winter period between years 2 and 3, the GAI achieves values greater than 3, when the over winter target was between 1 and 2. These excessively high GAI at this time result in biomass accumulation rates that are too high, hence AGB and therefore yield amounts in year 3 are too large (i.e. sowing years 2000 and 2001). Conversely, in some trials (i.e. sowing years 1994, 1995, 1996 and 1997), there was insufficient biomass to meet the parameter requirements for a cutting event, hence the yield value was recorded as 0. The model achieved stable simulations across all simulations for AGB, LGB and GAI (Fig. 47), for a four year simulation period.

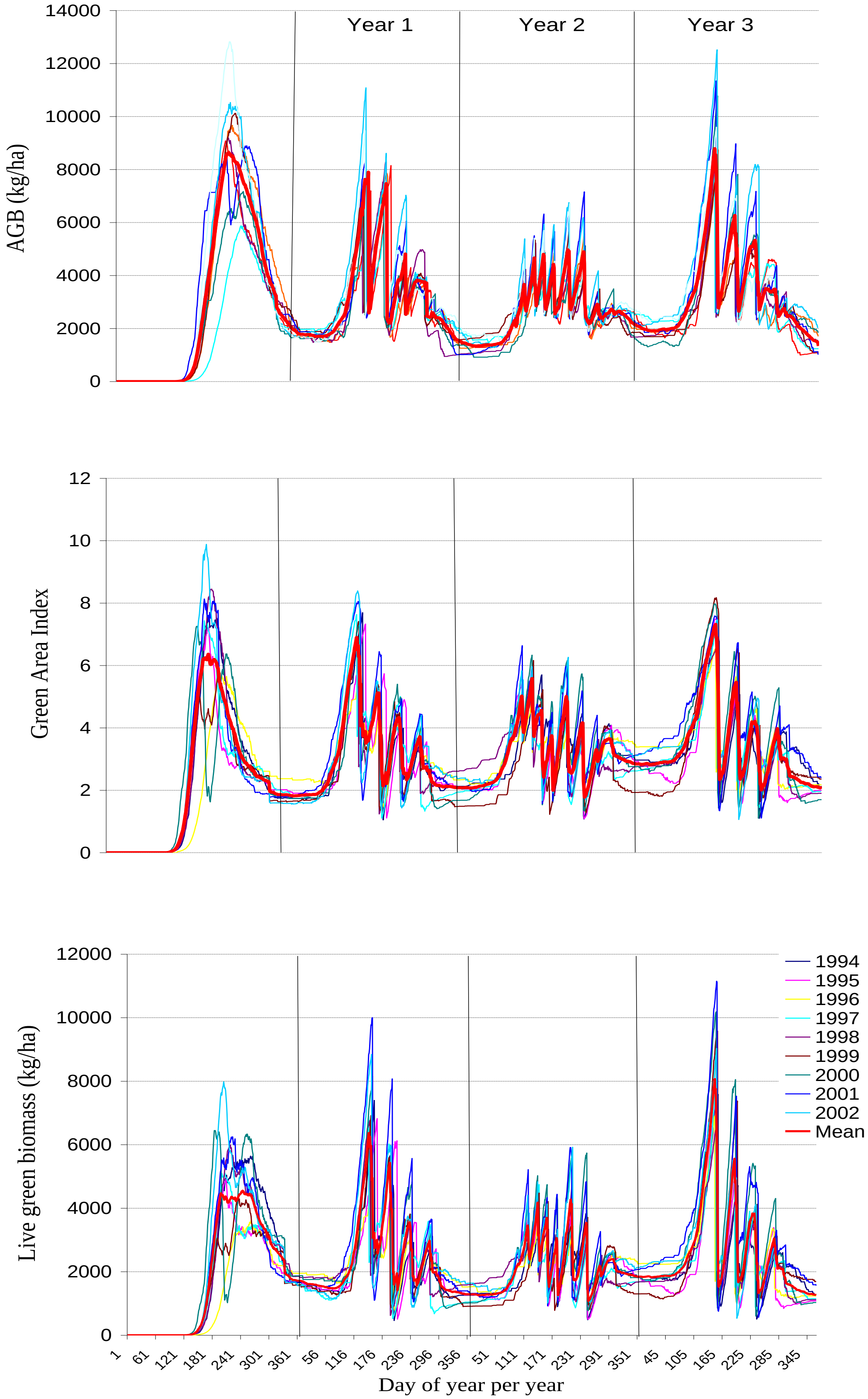


Figure 46. Estimates of Above Ground Biomass (top) Green Area Index (middle) and Live Green Biomass (bottom) per grass trial at Auchincruive

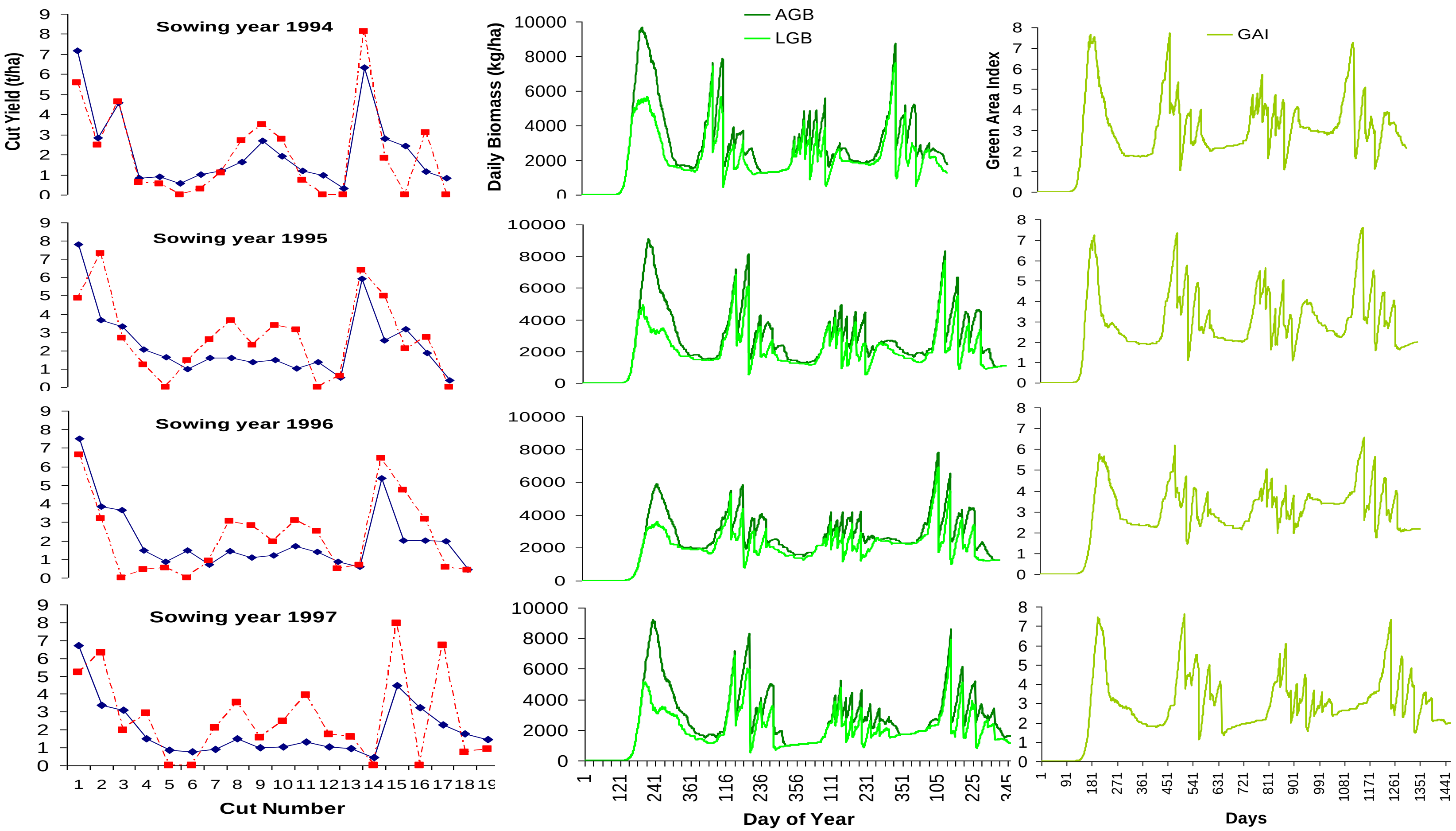


Figure 47. Left: Observed (blue) and modelled (red) yield per cut (t/ha) for each sowing year in the grass trials at Auchincruive.
Middle: Modelled Above Ground Biomass (AGB) and Live Green Biomass (LGB) corresponding to the sowing year
Right: Modelled Green Area Index (GAI) corresponding to the sowing year.

7.4.2 Grass trials evaluation at Bush.

At the Bush site, the model was better able to estimate the mean yields, particularly in the second half of year 2 (simulated grazing), but overall still failed to meet evaluation criteria 1. The estimates do meet the criteria 1 for individual cuts at Bush in: year 1 cut 2; year 2 cuts 6, 7 and 8; year 3 cut 2. The model under-estimated the large first cuts in years 1 and 3 (Fig. 48).

The model also failed to meet criteria 2 for the individual trials at Bush (Fig. 49), were the model generally under-estimated the cuts in year 1 (simulated silage conservation) and year 2, and was not able to reproduce the production patterns. In the third year of the trials, the model was able to reproduce the observed values well in some cases (i.e. trial sowing year 1996), whilst others had large errors (i.e. the under-estimations in trial sowing year 1994a).

At Bush (unlike at Auchincruive) the model was unable to maintain stable simulations of GAI and LGB (Fig. 50) in all years. The variability of LGB was too large, but which was not apparent in the variability seen in the AGB. This can be explained by an out of proportion balance between LGB and senesced material (AGB being made up of both).

Overall the pattern match was better at Bush than Auchincruive, but the magnitude of the errors was beyond the range of both the *a priori* criteria 1 and 2.

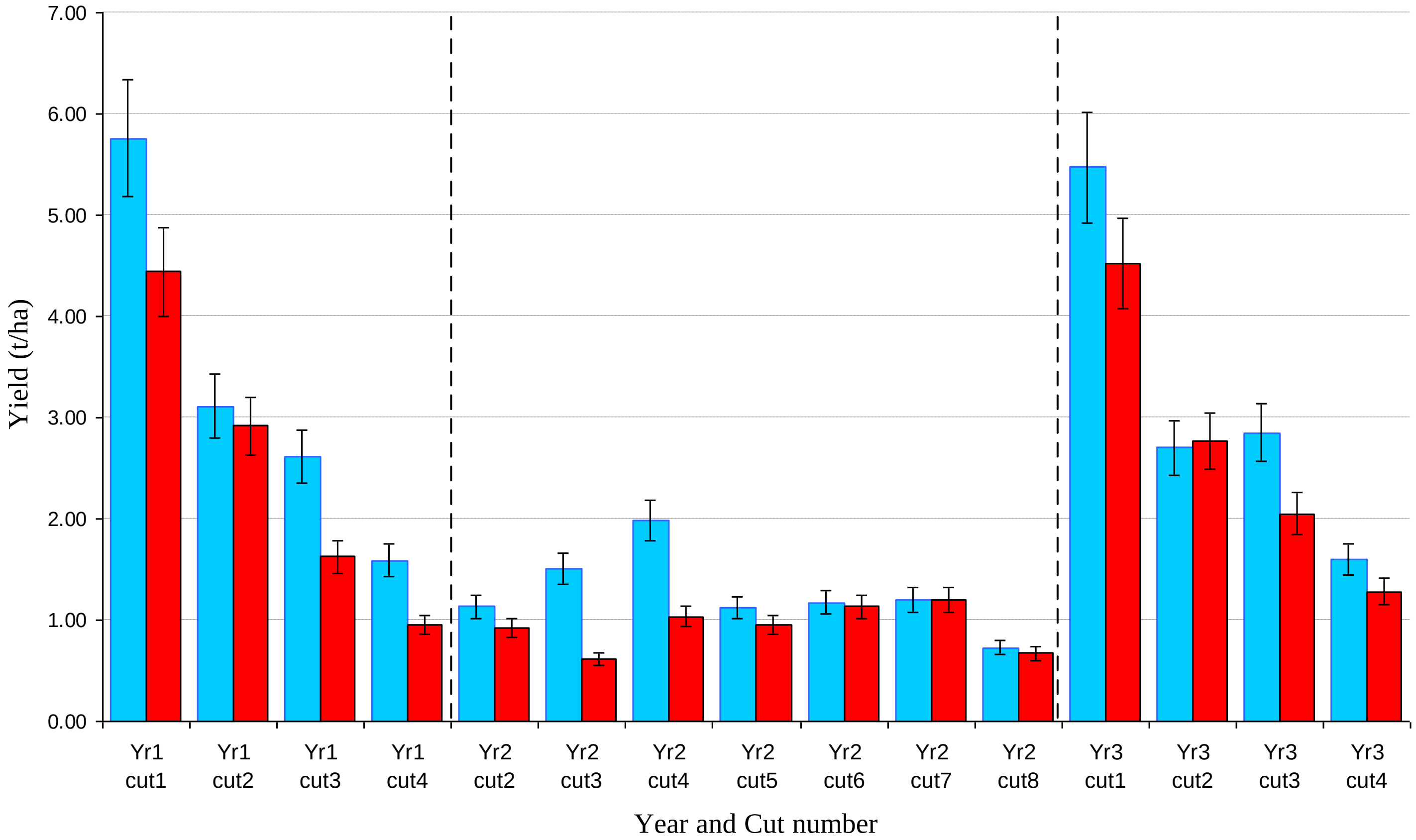


Figure 48. Observed (blue) mean yields per cut from the Scottish Agricultural College grass trials at Bush compared with CropSyst modelled mean estimates (red) derived using observed weather data. Bars show +/- 10% of the mean value.

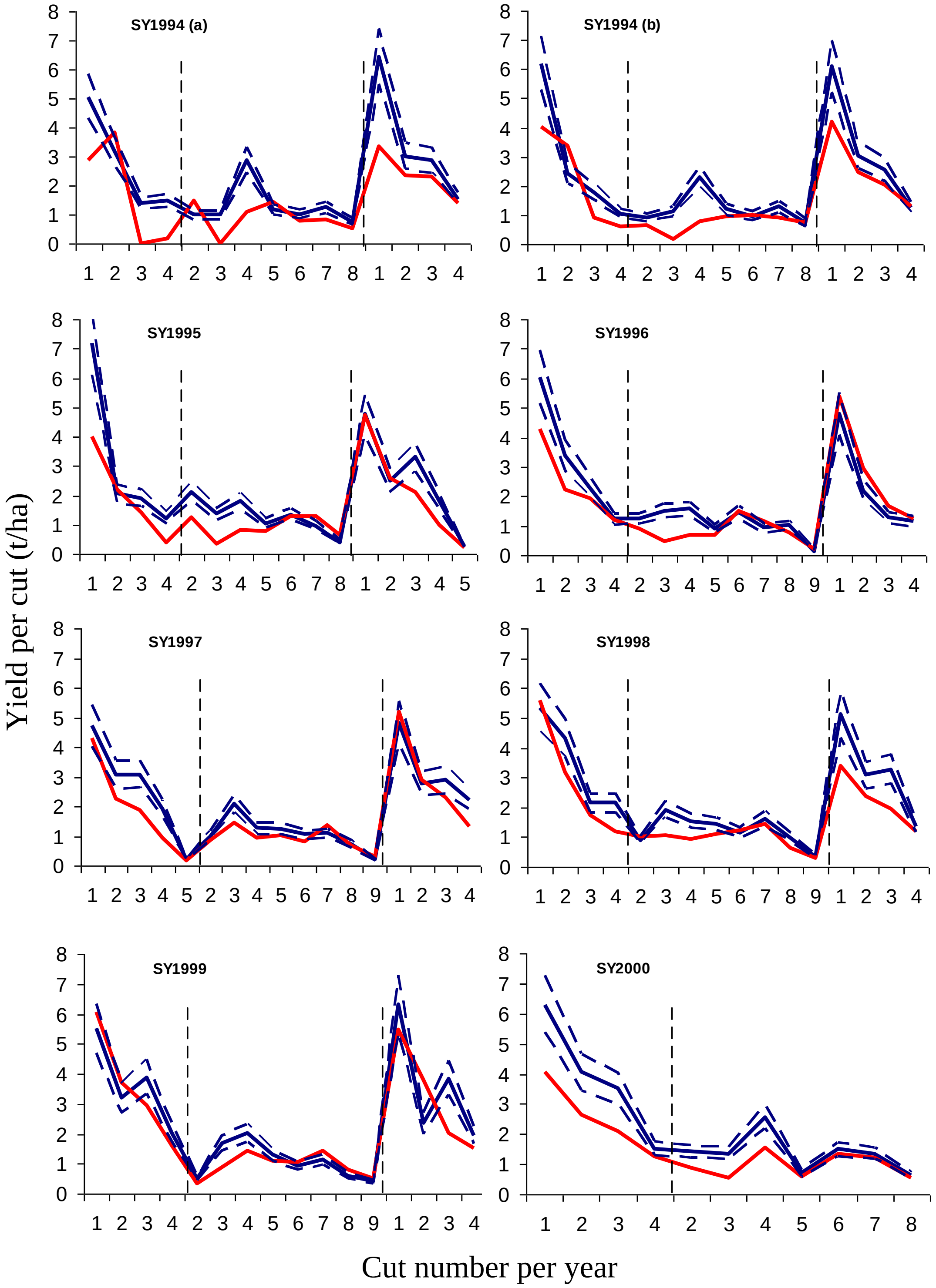


Figure 49. Observed (solid blue) with +/- 15% range (blue dashed) and estimated (red) yields per cut and year for each individual trial at Bush.
(SY = sowing year, dashed vertical lines separate years 1, 2 and 3)

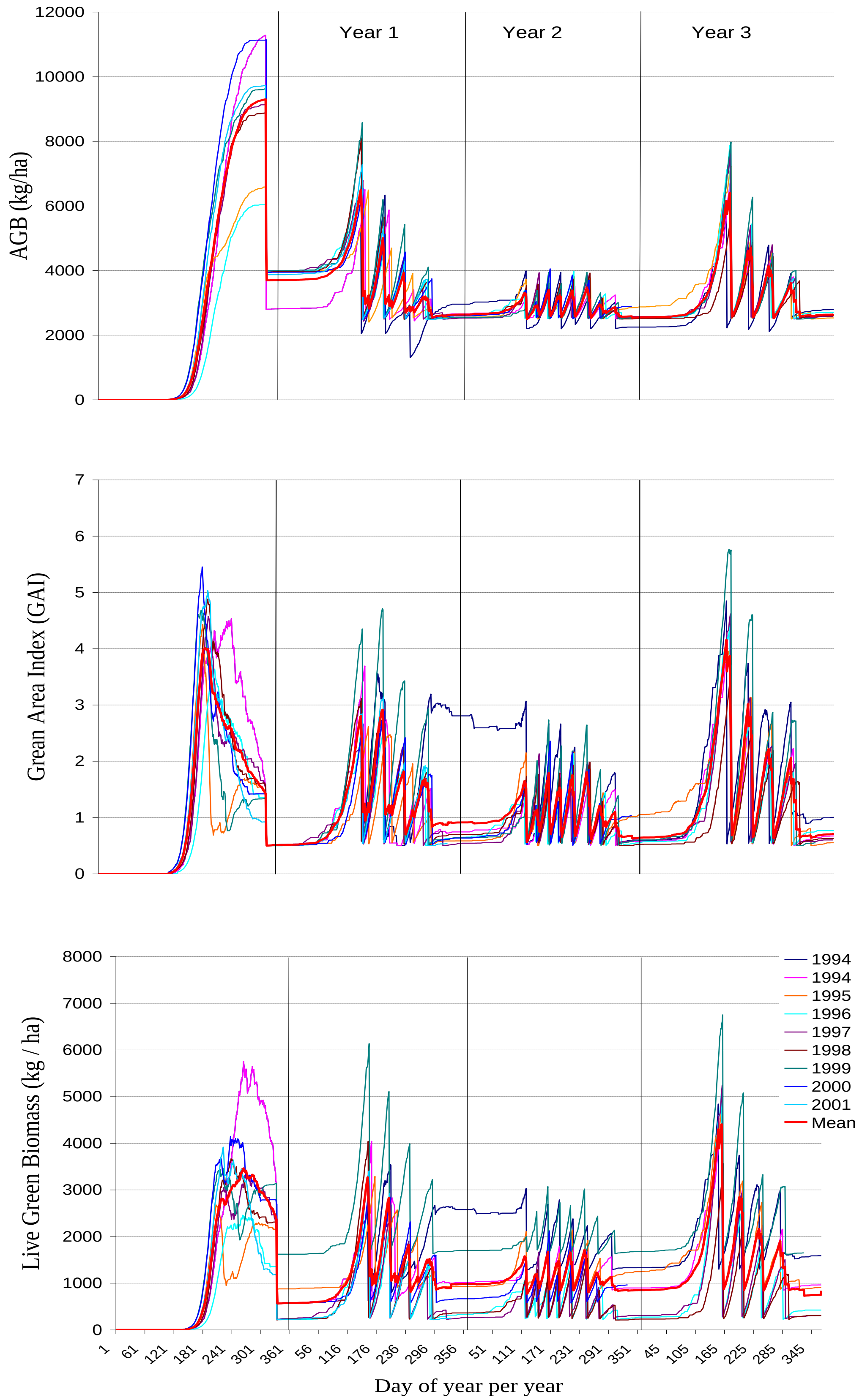


Figure 50. Estimates of Above Ground Biomass (top) Green Area Index (middle) and Live Green Biomass (bottom) per grass trial at Bush.

7.4.3 Grass trials evaluation at Aberdeen.

The model simulations of the grass trials at Aberdeen again failed to meet criteria 1. For the estimates of mean yields per cut, Aberdeen shows a similar response to Auchincruive, in that estimates for the later cuts in year 2 show large errors, whilst in the first and third years there are some individual yields that are within the +/- 10% range (year 1 cuts 1 and 3, year 3 cuts 1 and 3) (Fig. 51). In year 2 the simulated crop is accumulating biomass during the summer resulting in large yield values (mean of all cut yields = 3.035 t/ha), whereas the observed yields indicate that the crop was maintaining a consistently low amount of AGB (to give a mean of all cut yields = 1.153 t/ha).

At Aberdeen the model also failed to meet criteria 2 (Fig. 52). Growth in year 2 was excessive, with regrowth in the spring not being reduced by the early cuts, resulting in too large an AGB amount giving large yield over-estimations in the cuts towards the end of the year. As with the Auchincruive and Bush sites, the model did produce individual cut estimates that were within the criteria 2 range (+/- 15% of the observed value). However, in all trials at Aberdeen, the model was not able to reproduce the overall pattern of yields.

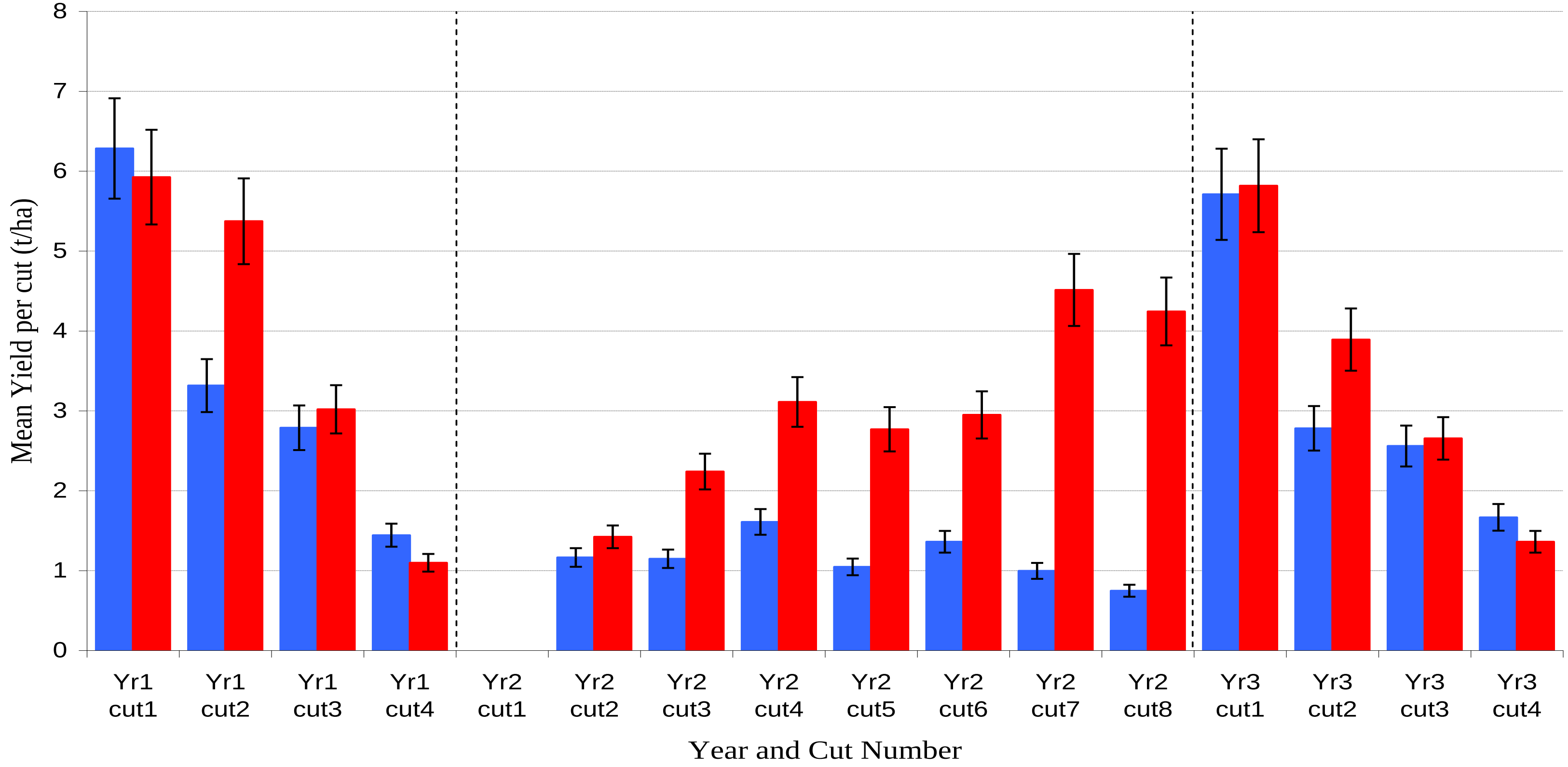


Figure 51. Observed (blue) mean yields per cut from the Scottish Agricultural College grass trials at Aberdeen compared with CropSyst modelled mean estimates (red) derived using observed weather data. Bars show +/- 10% of the mean value.

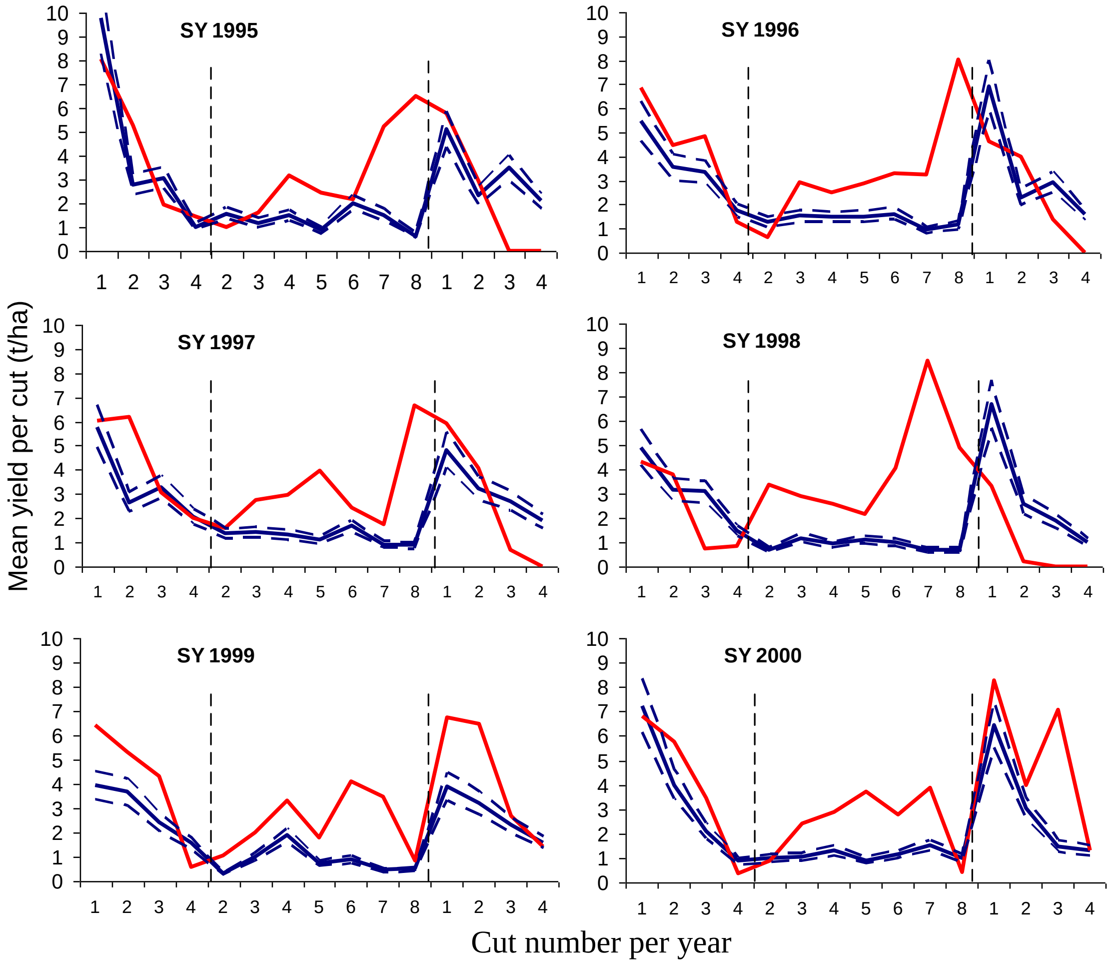


Figure 52. Observed (solid blue) with +/- 15% range (blue dashed) and estimated (red) yields per cut and year for each individual trial at Aberdeen.
(SY = sowing year, dashed vertical lines separate years 1, 2 and 3)

The model produced stable estimates of GAI, but had a wide range of over-winter values that varied between 1.15 (sowing year 2000) and 3.27 (sowing year 1999) between years 1 and 2, and 1.73 (sowing year 1999) and 4.47 (sowing year 1995) (Fig. 53). The over-winter amount of LGB also showed wide variation, falling to 0.635 t/ha (sowing year 2000) or reaching 2.392 t/ha (sowing year 1999) between years 1 and 2. A similar range was seen between years 2 and 3. There is a corresponding wide variation in the over-winter AGB.

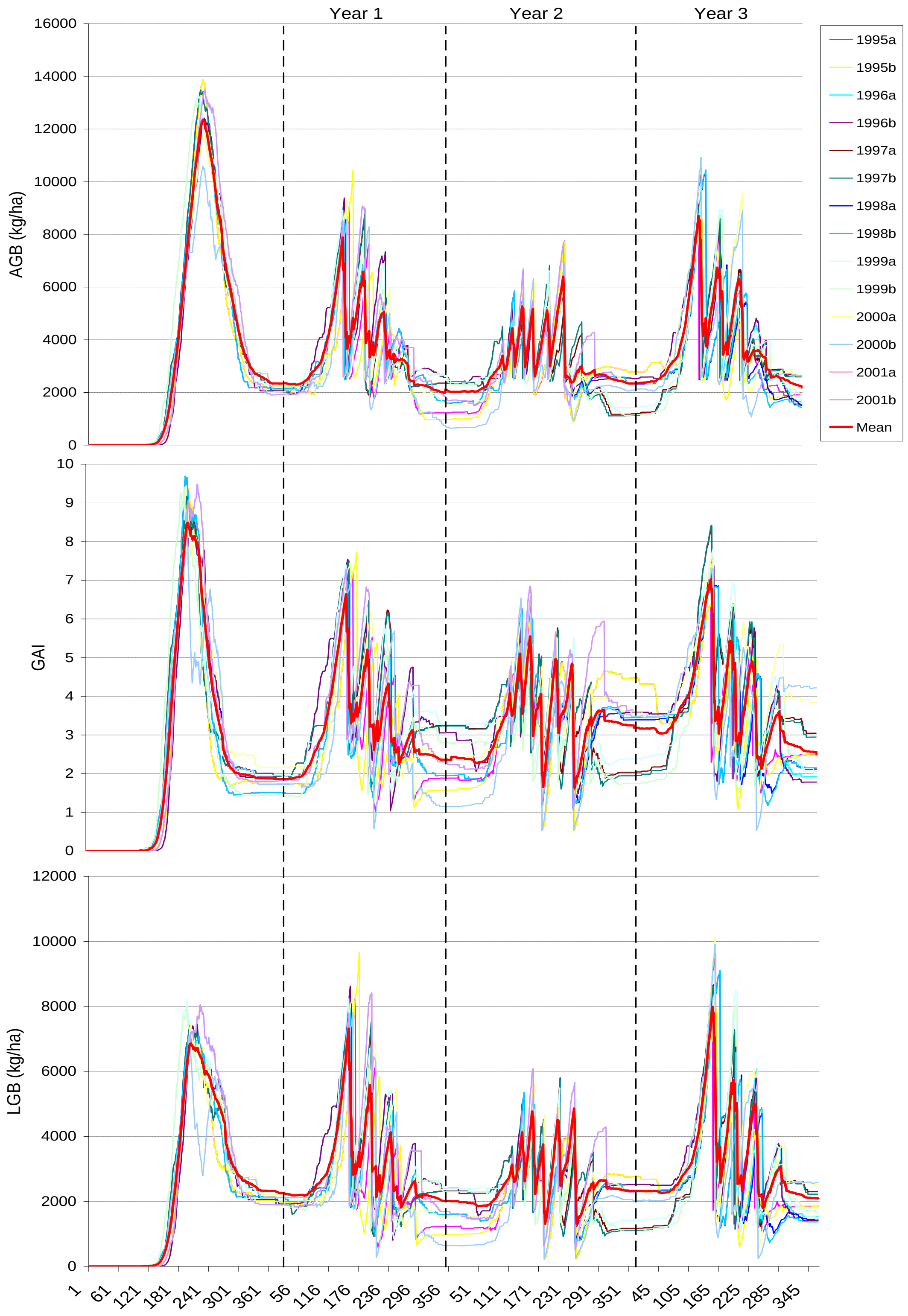


Figure 53. Estimates of Above Ground Biomass (top) Green Area Index (middle) and Live Green Biomass (bottom) per grass trial at Aberdeen.

7.4.4 Evaluation of modelled three cut silage system.

The model was unable to represent the observed mean of silage cuts from four fields at the Crichton Farm in 2007 (Fig. 54). There was however a wide variation in the observed yields between individual fields. The model was able to estimate the pattern of the first and second harvests (1^{st} larger than 2^{nd}), but under-estimated the mean first yield by 0.42 t/ha and over-estimated the second by 0.53 t/ha. Estimates for the third cut were an over-estimation by 2.83 t/ha.

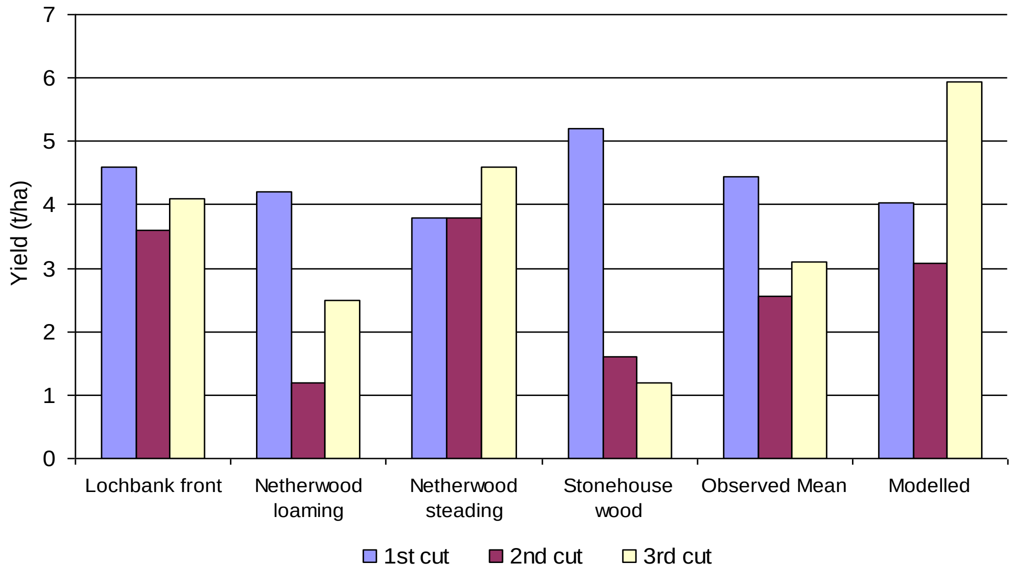


Figure 54. Observed yields from a three-cut silage system in four fields at the Crichton Farm near Dumfries in 2007, the observed mean and the CropSyst modelled estimates.

7.4.5 Grass production systems modelling.

7.4.5.1 Un-managed grass sward.

Using the Auchincruive site as an example, the model was able to produce stable estimates of acceptable magnitudes of AGB and LGB for the un-managed grass system using the observed weather data (Fig. 55), for about half of the simulation period, after which the values started to increase and loose stability. However, using the DsFP weather data, the

AGB and LGB estimates soon lost stability and achieved unrealistic magnitudes. Similar results were gained for Bush and Aberdeen.

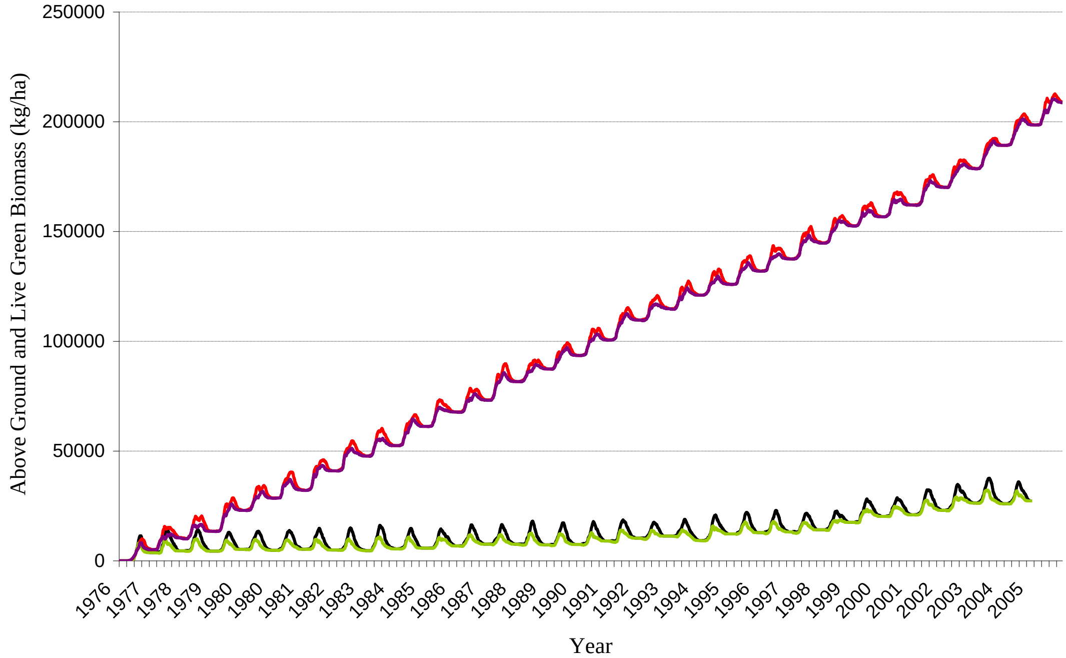


Figure 55. Modelled above ground biomass and live green biomass derived using observed (AGB = black, LGB = green, 1976-2005) and downscaled future projection (AGB = red, LGB = purple, 2070-2100) weather data at Auchincruive.

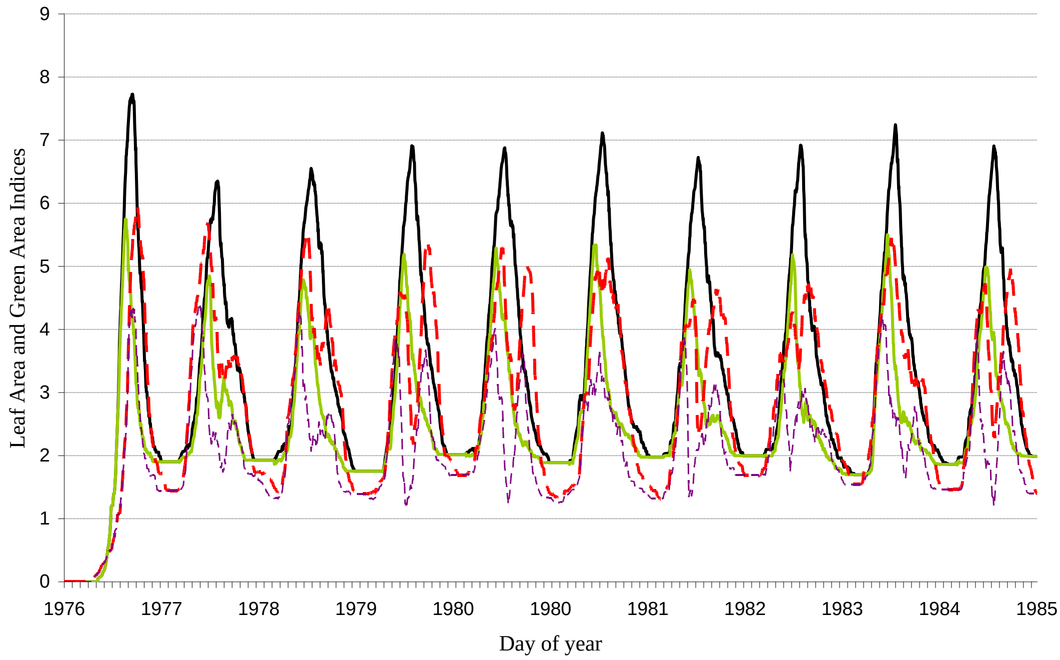


Figure 56. Modelled Leaf Area Index and Green Area Index derived using observed (LAI = black, GAI = green, 1976-1985) and downscaled future projection (LAI = dashed red, GAI = dashed purple, 2070-2079) weather data at Auchincruive.

Similarly the model produced stable estimates of LAI and GAI with realistic magnitudes with the observed weather data, but with the DsFP data the estimates, whilst maintaining similar but generally lower values to those from the observed weather data, developed an erratic pattern with sharp declines in the summer periods (Fig. 56). The main cause of these accumulated errors is the process of leaf senescence, where higher temperatures result in the thermal time accumulation controlled leaf duration (how long in degree days a leaf last for) being reached too early.

7.4.5.2 Silage systems.

Using the Bush site as an example, the modelled estimates of the one-cut silage system showed that the model was capable of producing AGB and LGB estimates with the observed weather data that were initially stable and representative of the patterns and magnitudes expected but lost stability as the simulation progressed, indicated by the trend line in Fig. 57. The simulation lost stability much earlier with the DsFP weather data.

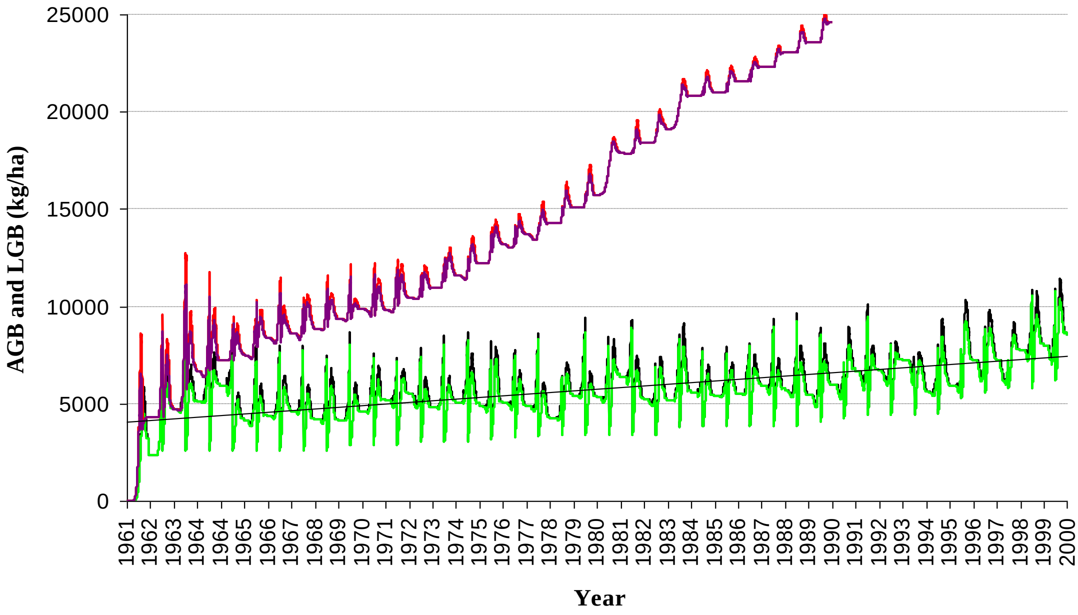


Figure 57. Estimated Above Ground Biomass (AGB) and Live Green Biomass (LGB) for a one-cut silage system at Bush, derived from observed (AGB = black, LGB = green) and downscaled future projection (AGB = red, LGB = purple) weather data. The trend line shows

the instability of the simulation in AGB and LGB resulting from use of the observed weather data.

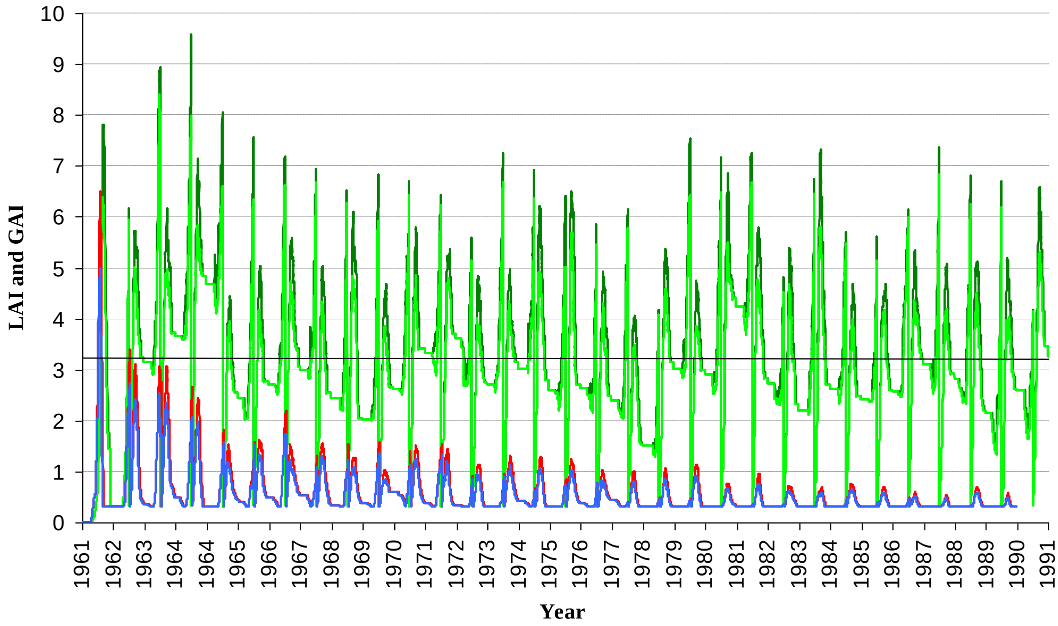


Figure 58. Estimated Leaf Area Index (LAI) and Green Area Index (GAI) for a one-cut silage system at Bush, derived from observed (LAI = dark green, GAI = light green) and downscaled future projection (LAI = red, GAI = blue) weather data. The trend line shows the stability of the simulation in representing LAI and GAI using the observed weather data.

For LAI and GAI, the model was able to produce stable estimates for the entire simulation using the observed weather data (but with values that were too high in the first 3 – 6 years) (Fig. 58). However, this did not translate to stable AGB values (Fig. 57). Using the DsFP the estimates of LAI and GAI lost stability from the second year (Fig. 58), with a decline in values, which is in contrast to the increase seen in the AGB. Similar patterns of estimate instability and magnitude errors were seen at other locations.

7.4.5.3 Artificial grazing regime simulation.

In representing the artificial grazing regime, the model was able to produce estimates that appeared to maintain a sward biomass capable of sustaining the number of livestock set in the simulation (equivalent to 100kg/ha/day off-take) (Fig. 59).

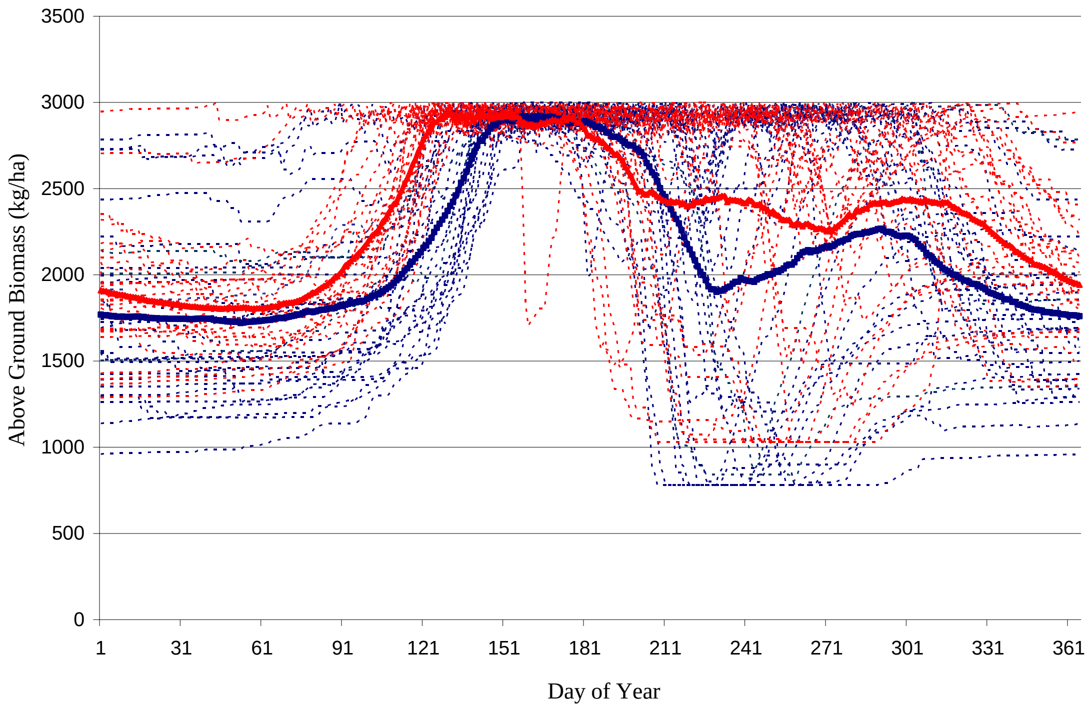


Figure 59. Estimates of above ground biomass (kg/ha) in an artificial livestock grazing simulation using observed (1960-1990, mean = solid blue, yearly = dashed blue) and downscaled future projection (2070-2100, mean = solid red, yearly = dashed red) weather data for Aberdeen.

However, though the mean AGB derived from both observed and DsFP weather data appears to follow a realistic pattern, individual years showed a wide range in variability. Estimates of LAI and LGB maintained values between 1 and 3, following a pattern similar to that of the AGB, with sharp sudden declines and increases in the summer and autumn period. Similar results were gained from simulations at Bush and Auchincruive (not shown).

7.5 Discussion.

7.5.1 Model evaluation.

Based on the *a priori* evaluation criteria, the model was unable to represent grass growth sufficiently well. The results show that whilst the model was able to represent an approximation of some of the forms of grass production, it currently lacks the appropriate structure and level of parameterisation effort in order to produce estimates with acceptable accuracy and precision. The main cause of discrepancies was due to an inability to adequately represent the process of leaf emergence and senescence, coupled with the fact the model does not contain functions for material translocation from roots to stems and leaves. This situation forces the need to artificially manage the AGB, particularly over the winter period, and the GAI so that the crop has sufficient AGB and GAI for new growth to start from. The estimates made at the start of each year of the trials were sensitive to the amount of AGB and GAI remaining over the winter. However, this does partially reflect actual growth characteristics that are dependent on the quality and health of the sward in the previous year (Alan Sibbald, pers. com).

Whilst the model has a good level of flexibility in the way simulations can be set up, the parameters used in these evaluations pose constraints on responses to harvesting. For example, some modelled trial cutting events were recorded as 0 yields, as the parameters were set such that a minimum AGB and GAI would remain (so the crop had material on which to base re-growth). The model was also sensitive to the level of nitrogen and water stress. Without adequate observed data on soil moisture and nitrogen status it was not possible to determine whether the model was inadequate at representing soil water and nitrogen processes, or that the crop parameters were incorrect leading to unrealistic water and nitrogen demand.

Some of the results indicate that the delicate balance of parameters could be achieved so as to produce estimates that are a close (meeting some of the *a priori* criteria) approximation to observed yields (i.e. Auchincruive sowing year 1999 – Fig. 45). Overall however, the combination of structural inadequacies, parameter sensitivity and interdependence meant the model lacked the consistency of close approximations, showing instead a wide range in variability that also lacked uniformity in the magnitude and pattern of errors. The non-modular structure of the version of CropSyst used means that the extent of errors occurring in sub-models (water transport, nitrogen and organic matter pools in the soil, evapotranspiration etc.) and how they manifest themselves within estimates of crop growth could not be evaluated. This situation makes identifying the cause of errors in AGB problematic, though the evidence from the results indicates that the errors arise from a combination of sources, rather than a single component of the model.

The evaluation of the model using the SAC trials is further complicated by issues of uncertainty in the quality of the observed yield data. The number of cuts made varied between years and sites. An informal source of information indicated that the observed yield values were occasionally aggregated, thus distorting the total individual cut amount.

For the Crichton Farm data, a large variation is seen in the observed yields per field. Accurate representation of such variation would seem to be overly demanding of the model, given that the same soils and weather data were used. This serves as an illustration of the variability of grass growth and the difficulties of modelling it.

7.5.2 Representation of grass production systems.

Beyond the use of observed data from the SAC trials and Crichton data, the modelling of grass systems had a mixed performance. Using the observed weather data gave estimates of continuous un-managed grass growth that initially had stable AGB and LGB, and with continuously stable LAI and GAI values. The gradual loss of stability in the AGB estimates meant the crop was accumulating biomass from one year to the next. This was a function of an imbalance between the amount of biomass accumulated over individual growing seasons and the amount senesced. The primary driving parameters controlling these were the thermal time of leaf duration (how long leaf material remains on the plant in a productive capacity) and those that control senescence. Leaf area development depends on daily biomass production. However, because leaf expansion is reduced and stopped earlier than biomass production under water stress conditions, GAI calculations are not directly dependent on AGB production, but rather on an auxiliary variable defined as the leaf area expansion-related biomass production (LAERB). This quantity is only accumulated when the ratio of actual to potential transpiration is greater than the crop water stress threshold defined by the 'actual transpiration : potential transpiration ratio where leaf area growth ceases' crop parameter. Given this calculation method, it was possible to achieve increasing biomass but with a decreasing, and in some cases, erratic GAI (i.e. Figs, 56, 57 and 58) if the ratio parameter is incorrect.

Also, the model does not represent re-mobilisation of plant resources between roots and AGB. Instead, once root biomass has reached a potential maximum, it remains there, without translocation to AGB in the spring, and without additional AGB being translocated to roots. A further contributing factor is the sensitivity of the model to the amount of AGB over the winter period and therefore the mount available to initiate re-growth.

Whilst it was possible to achieve a near-stable simulation with credible GAI values using observed weather data for the un-managed grass simulation, the more favourable growing conditions contained within the DsFP weather data produced the unstable simulation results. Though the poor quality of estimates for growth under the future climate negates their use in making detailed projections, the results did give an indication that grass growth over the winter may be more common under the future climate.

For the silage and grazing simulations, the underlying faults in the representation of grass growth are further distorted by the cutting events which effectively reset phenological development and leaf duration values. Whilst the basis for errors and instability seen in the silage system remains as for the un-managed system, the grass trials results indicate that the model was capable, to a limited extent, of represent the AGB responses to cutting or grazing. However, the individual SAC trials were for four years only, whilst the silage and grazing simulations were for 30 years. This gave the simulations longer in which to loose stability.

Despite the overall poor quality of estimates made by the model under the future climate scenario, the work undertaken did provide indications of some potential impacts. Higher levels of water stress in the future, particularly in the summer, may restrict grass growth and so limit options for grazing animals. This raises the potential for livestock to required additional feed during dry summer periods. Conversely, additional grazing material may be available bother earlier and later in the growing season. In the absence of water stress, higher silage yields are possible, or harvest may be conducted earlier in the year giving rise to the possibility of additional silage cuts being made. However, considerations would have to be given to the effect on feed quality.

7.6 Conclusions.

The version of CropSyst used to estimate grass growth lacked the appropriate structure to enable estimates with a suitable degree of utility to be produced. This reflects the complexity of grass growth and plasticity of responses to differing types and intensities of management and disturbance. CropSyst was not originally designed to represent perennial crops like grass, but has successfully been adapted to include crops such as tea and grapes. However, the wider range of management and harvesting methods for grass and plasticity of growth responses means that developing an appropriate structure within an existing model is highly problematic. The model needs to include functions for translocation of biomass from roots to stems and leaves, and back again, and with better representation of root mortality. Also, greater control over how senesced material is handled (rate and timing) will facilitate achieving a balance between AGB production and senescence over a single year. It must be concluded that the current version of CropSyst is not capable of producing estimates for grass systems with an acceptable degree of utility for either the current or future climate.

Whilst there was some degree of success in adapting CropSyst to represent grass systems, in that the model was capable of estimating approximate patterns and magnitudes of growth, the calibration was based on a limited data set. Further investment in collating a better integrated calibration data set (to include measured above ground biomass, leaf area index, root biomass, ratio of live to senesced leaf material and soil water and nitrogen) would facilitate a higher quality of parameterisation. Time spent in developing the model structure, calculation methods and parameter interactions could lead to the development of a model capable of representing generic single species grass production systems, but not one able to represent the fine details of grass growth dynamics. This would not however overcome the problems of modelling complex species interactions within a grass sward, or the nutrient dynamics of grass and clover mixes. To achieve these capabilities a considerable development effort would be required. That said, other models developed specifically for grass would also have presented challenges for calibration, and without any guarantee of achievement of the *a priori* evaluation criteria.

The inability of the current state of development of CropSyst to represent grass systems prevents the use of the estimates within the wider farm-scale model. The work conducted as part of this Chapter has been unable to provide any evidence as to how grass productions systems may change under a future climate, only some possible indications. It would therefore be inappropriate to estimate projected changes in livestock systems without a useable evidence base of changes in grass production. The investigations using CropSyst did provide some poorly defined indications as to how grass growth may be affected under the future climate. However, these indications (higher water stress in the summer, earlier and later growth in the growing season, and some growth over the winter) are in broad agreement with the evidence from the agro-meteorological metrics in Chapter 5.

Chapter 8: Discussion and Conclusions.

The aim of this thesis was to examine the uncertainty associated with modelling the impacts of climate change on farm scale dynamics. The aspiration had been to conduct whole farm simulations using the LADSS modelling tools, but this was constrained by the path dependencies of developing the grass modelling capabilities in order to adequately represent livestock-grass interactions (see Figure 1). Given that I was unable to complete to ful set of original objectives, the purpose of this final Chapter is to place the research findings that have been achieved within the context of resilience and adaptive capacity, and to summarise the best possible indication of potential impacts.

8.1 Key issues.

- The results are based on a single climate model and emissions scenario.
- Whilst there is uncertainty associated with climate science and climate modelling, simple evaluation and downscaling approaches used increased the utility of projected climate data and therefore their credibility for use in impacts assessment.
- The estimates available for future weather conditions, when used in a range of modelling tools, do provide valuable insights into how impacts on farm dynamics will manifest themselves.
- Care has to be taken in interpreting the estimates made by models simulating the response to future climate conditions due to input data error manifestation.
- Estimates of crop production were made without including modelled responses to elevated CO_2, hence yield values presented here may be under-estimated.

8.2 Key findings.

- With respect to Scottish farm type's resilience to the impacts, this work indicates that primary production levels can be either maintained or even increased using suitable management adaptations and that the biophysical constraints to crop growth, whilst potentially of greater variability, will not prevent agricultural activity.
- Hence existing systems have the basis to remain resilient through their capacity to adapt and able to cope with the biophysical impacts of climate change based on a 2-3 degree warming (as per the A2 emissions scenario) in the next 40-50 years (but not considering the specific farm financial, infrastructure, skills and labour constraints, impacts of pests or diseases, or impacts external to Scotland).
- The biophysical impacts of a changed climate in Scotland present both risks and opportunities for agricultural based land uses.
- Opportunities include increases in crop productivity due to a reduction in climatic constraints, requiring cultivar based adaptation.
- There will also be additional challenges in management decision making based on increased constraints determined by soil water availability.
- The above will require some substantial alterations to existing land use management practices to optimise the benefits and minimise the risks.
- This study has demonstrated the value in taking an integrated approach to explore complex inter-related issues. Using a suite of simple to complex models allows a broad picture to be created with specific details available where modelling capabilities permit.

8.3 Summary of results.

This study has demonstrated the value in following an approach of uncertainty evaluation (climate model assessment and downscaling, and introduced uncertainty in crop models), and land use modelling at an increasing level of complexity. The results show that the HadRM3 was capable of making both good and poor hindcast estimates of weather variables at different sites in the UK. The estimates for the hindcast period were sufficiently close to observed data to permit bias correction giving a better match between modelled and observed data. The downscaling process, when applied to future projections data, helps increase confidence in the utility of the data for use in secondary modelling efforts. Chapter 4 demonstrated the value in undertaking uncertainty assessment approaches to ensure that false conclusions were not drawn from the use of climate model data within a cropping systems model. The findings indicate that great care is needed in interpreting the estimates made by crop models of future productivity, arising from introduced uncertainty by different types of weather data. The work undertaken in Chapter 4 emphasises the need for careful model calibration and validation. In the case of making projections of future productivity, validation should also include an assessment of data source introduced uncertainty and inclusion of crop physiological responses to elevated CO_2.

The agro-meteorological metrics demonstrated that whilst the overall perception may be that climatic constraints on Scottish agriculture may be eased, future higher levels of water stress will impose a different aspect to restrictions on plant growth (backed up by CropSyst estimates in Chapter 6). The agro-metrics indicate the potential for opportunities for adaptations within farming systems, such as a longer growing season, possible reduced frost risk (with the caveat that the HadRM3 was shown not to be good at estimating extreme cold conditions), and drier soil conditions in autumn. The constancy into the future of the date of the end of field capacity may present challenges in how to optimise the benefits of favourable growing conditions in spring whilst dealing with issues of access and trafficability. The crop modelling assessment in Chapter 6 has shown that potential exists to make the most of higher temperatures by developing cultivars with slower phenological development. However, such new cultivars will also need to have improved water and nitrogen use efficiency, building on the possible positive effects of elevated CO_2. Under the climate scenario used, spring barley and winter wheat will continue to be viable land uses in Scotland. Given the values presented for yield may be under-estimates as they were derived without using CropSyst's functions for including elevated CO_2 effects, and given the evidence presented in Chapter 2, section 2.8, future cereal yields in Scotland may be higher than indicated by this research. The results indicate that changes to management may be required, in terms of timings of sowing and harvest to avoid unfavourable weather conditions and in efforts to improve soil moisture retention and nitrogen content (i.e. by maintaining higher soil organic matter). The potential increase in yields in Scotland may give a competitive advantage over other areas in the UK and elsewhere, where yields may decrease due to high water stress.

Efforts to develop the grass modelling capabilities of CropSyst failed to result in an acceptable quality of estimates (Chapter 7). Whilst this was a disappointment, it did reflect the difficulties of simulating a complex set of processes for a crop with high plasticity in its responses to the environment and management. The representation of grass ould further have been complicated by the uncertainties associated with the crop's response to elevated CO_2 (i.e. increased tillering). Similarly it highlighted the risks of path dependency in an Integrated Assessment approach using an IMF. The poor quality of estimates made by CropSyst of grass growth resulted in the decision not to use them within the whole farm model. This, coupled with technical issues of running the whole farm model and the time required by other people to initialise and run simulations, prevented the completion of the 'simple to complex' spectrum of modelling approaches. What this overall study has demonstrated though is the value in having an Integrated Assessment approach made up of a range of tools operating at different levels of complexity (on the basis that simple tools have lower data, skill and researcher time requirements). The findings presented here indicate that valuable insights can still be gained, even when complex tools are not used.

8.3 Findings in the context of resilience and adaptive capacity.

This study was focused on the evaluation of uncertainty in modelling the impacts of climate change on field and farm scale dynamics of agricultural production. Referring back to Gunderson and Hollings' statement (2002) that to understand socio-ecological systems it is necessary to consider multiple scales of time, space and social organisation, the findings presented in this study indicate that basic essential elements of primary production within farming systems in Scotland (as part of socio-ecological systems) are likely to experience climate change impacts that, whilst requiring substantial changes to crop choice, crop cultivar selection and management, and potentially the mix of land uses within a farm, are within the scope of adaptations. Given the findings from this research and the magnitude of some of the changes, it is entirely plausible that many farm businesses will not be able to cope with the impacts and the costs of adaptations. However, it is also plausible that those businesses able to make the required adaptations will also be able to expand and take over financially insecure businesses. Overall, they are therefore likely to underpin the higher levels within the socio-ecological scales in terms of maintenance of viability at the Scotland scale, though change may also be required to supply chain systems resulting from an altered range of agricultural products. Had the modelling estimates of primary production indicated a decline in productivity and the agro-meteorological metrics pointed towards increasing climatic constraints (as opposed to the shift in balance of constraints seen, for example towards increasing water limitations but with warmer temperatures), then the conclusion would have been to the contrary. Decreasing productivity and more severe climatic constraints would potentially mean greater financial pressures, though higher commodity prices on a global scale due to decreased supply and higher demand may counter this. If productivity remains either stable or increases, and given higher commodity prices increase, then the costs of adaptation will be more easily bourn by Scottish agricultural businesses.

Whilst the focus of this study has only been at the field and farm scale, the work has shown the value of the resilience and adaptive capacity concept in organising assessments of climate change impacts and envisaging adaptation options to be placed in a wider range of spatio-temporal scales. Continuation of this study could aim to quantify impacts at higher spatial and organisational scales. As such the type of study undertaken here can serve as a basis in supporting studies looking at parts higher up the socio-ecological system hierarchy, i.e. as a structured scenario (as per Folke *et al.* 2002), helping to inform active adaptive management.

8.4 Specific and system wide adaptations.

It is important to distinguish the need for specific adaptation options (such as crop cultivar traits to utilise elevated CO_2 responses or to cope with more rapid phenological development, soil moisture conservation management etc..), and those that address the system wide range of threats and opportunities arising from changes in economics and policies. The combination of both specific and system wide adaptations must seek to ensure that the farm system can maintain flexibility to cope with changing circumstances whilst preserving the main capitals and functions making up the system. The 'system' of any particular farm will however, be at a different phase (in the adaptive cycle) from other farm types and locations. The results here indicate that Scottish systems may be more stable (in the exploitation leading to consolidation phase) than those in other locations where impacts are more severe (where the consolidation phase experiences creative destruction). The point here is that the relatively low levels of impacts in Scotland will put farming systems at a different phase from those where impacts require more drastic adaptations.

Specific adaptations may become insignificant or irrelevant in the face of pressures from the need for fundamental changes in farming practises arising from the larger external drivers, such as national or international policies and economics. However, the specific adaptations will be the foundations on which existing practises can evolve to cope with changes, but there will be thresholds to how much the specific adaptations can develop, which will set the boundaries for when an existing system remains viable. Put another way, there is only so far that an existing system can adapt before it either becomes biophysically impractical or economically infeasible. The findings of this study indicate that in Scotland, the changes resulting purely from alterations of the biophysical environment are within the scope of adaptive capacity due to the potential of specific adaptation options. That is not to say that there will not be increased risk due to changes in weather variability (giving extreme events). The combination of altered weather variability and adaptation options are likely to change the appearance of farming practices (i.e. silage conservation for summer feeding, reduced animal grazing during dry periods, rotations including novel crops, etc..), but overall the farming system types will likely remain similar to their current appearance.

It has been beyond the scope of this study to quantify the impacts from external drivers such as global or national scale economics or policies. Hence the contrast between short-term resilience and long-term adaptive capacity (highlighted by Easterling 1996 in Chapter 1) indicates the need for flexibility in resilience to allow transition from one farm system state to another in order to allow the changes required to adjust to the external large scale drivers. Such evolution of adjustments are likely to occur at differing rates dependent on many factors, including social (farmer preferences, skill, experience and foresight), financial state of the farm business (access to finance, savings etc..) and on-farm biophysical resources. This emphasises the importance of social co-learning between researchers, practitioners and communicators / educators in developing flexible adaptation options and for policy makers to facilitate up-take and application of good practise.

Agriculture differs from most other business sectors in that there will always be a demand for agricultural produce. Taking this into account and based on the results found here, considering the fundamentals of primary production, that Scotland’s potential benefit from an easing of climatic constraints will also make Scottish agriculture more resilient to large scale external drivers. Whilst Scotland may experience some negative effects of extreme events, and increased risks due to pests and diseases, proportionally it is likely to be less than other agricultural areas. This is reflected in the additional levels of water stress restricting crop production in southern UK.

8.5 Critique of the study.

The results given in this study are based on the use of climate projections from a single climate model and for only one emissions scenario and time slice (A2 for 2070-2100). The variability in estimates made by the land use models is therefore limited to the variability of the single model, scenario and time slice combination. This permits only a narrow view of the uncertainty associated with climate modelling and in estimating future land use responses. A more comprehensive study could have used data from multiple models, scenarios and time slices, giving a broader range of model, scenario and time slice combinations. An initial plan for the study had been to use the climate model ensemble derived UK probabilistic climate projections due for release in 2008. Unfortunately the data was not available until June 2009, preventing estimates of crop production and agro-metrics based on probability distributions. The results gained from the single climate model and scenario and spectrum of land use models, are however useful indications as to the potential impacts and serve as a valuable starting point in developing adaptation strategies. Improvements to the study and further developments of the work would include the use of the UKCP09 (DEFRA 2009) probabilistic projections (based on large climate model ensemble simulations) in order to estimate probability distributions of crop model estimates and agro-meteorological metrics values for a wider range of emissions scenarios and time slices. An expansion of the work would also need to include making the estimates made spatial, to give a better overall representation across Scotland. However, the use of the

UKCP09 data would not have resolved the issues of crop model validation and the evaluation of the manifestation of errors would have been made more problematic due to the larger amount of estimates made. Hence new techniques will be required to evaluate error propagation within environmental models from using probabilistic data.

Fundamental to improving the ability to better understand the impacts of climate change on Scottish agriculture, is the need to be able to model grass based production systems. The failure to develop CropSyst grass modelling capabilities to an acceptable standard was due to several reasons: the limitations of working with a generic model structure not specifically designed for grass simulation; limited skill in parameterising the model within its structural constraints; the lack of good calibration data; and the difficulties in representing a crop with high levels of plasticity in responses to environment and management. The role of grass modelling in the path dependency of using a complex whole farm model highlights the need to get the basics right in order to avoid the propagation of errors into the more complex models. Further to this, there is a requirement to improve crop simulation models, so as to better represent the combinations of plant responses to elevated CO_2, water and nitrogen availability and temperature extremes.

8.6 Conclusions.

Climate change impacts on farm scale dynamics in Scotland are likely to require a range of alterations to management practises, but these adaptations are within the scope of the adaptive capacity of farming systems. This is based on the use of the agro-meteorological metrics to indicate an easing of climatic constraints to primary production, and crop modelled projections that primary productivity can increase in the future in Scotland. This conclusion though has to be viewed in light of the impacts of possible other, large and more significant drivers of change such as economics and policies at national and international scales.

Whilst there is likely to be an easing of climatic constraints to agricultural production, these benefits may be balanced against potential increases of risk arising from changed weather variability. Though not considered in this study, there are likely to be other negative impacts from increased damage caused by pests and pathogens associated with an easing in climatic constraints.

The credibility of these conclusions is aided by the approach taken in this study of climate model evaluation, downscaling and assessment of introduced errors to a crop model so as to address issues of uncertainty, and use of multiple tools on a spectrum of representation complexity. The approach taken highlighted the limitations of climate model data use and the potential for bias correction of future estimates based on observed versus model hindcast differences. Using a crop model and agro-meteorological metrics enabled a more comprehensive picture to be formed of potential future impacts. However, substantial uncertainty remains in terms of modelling crop responses to the combinations of elevated CO_2, water and nitrogen availability and extreme temperatures. The work presented here gives an indication of crop responses, which may have under-estimated yields, but pointed to directions of change. The challenge for farmers in Scotland now is to use such information to guide them through the transformational change required to cope with the biophysical, economic and policy impacts of climate change.

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Appendix: Published Papers

(see attached CD)